

SENSORS & TRANSDUCERS

ISSN 1726-5479

vol. 252
5/21

Sensors, Measurements & Networks

International Frequency Sensor Association Publishing



Sensors & Transducers

**International Official Open Access Journal of the
International Frequency Sensor Association (IFSA)
Devoted to Research and Development
of Sensors and Transducers**

Volume 252, Issue 5, October 2021

Editor-in-Chief

Prof., Dr. Sergey Y. YURISH



IFSA Publishing: Barcelona • Toronto

Sensors & Transducers is an open access journal which means that all content (article by article) is freely available without charge to the user or his/her institution. Users are allowed to read, download, copy, distribute, print, search, or link to the full texts of the articles, or use them for any other lawful purpose, without asking prior permission from the publisher or the author. This is in accordance with the BOAI definition of open access. Authors who publish articles in *Sensors & Transducers* journal retain the copyrights of their articles. The *Sensors & Transducers* journal operates under the Creative Commons License CC-BY.

Notice: No responsibility is assumed by the Publisher for any injury and/or damage to persons or property as a matter of products liability, negligence or otherwise, or from any use or operation of any methods, products, instructions or ideas contained in the material herein.

Published by International Frequency Sensor Association (IFSA) Publishing. Printed in the USA.





Editors-in-Chief: Professor, Dr. Sergey Y. Yurish, tel.: +34 696067716, e-mail: editor@sensorsportal.com

Editors for Western Europe

Meijer, Gerard C.M., Delft Univ. of Technology, The Netherlands
Ferrari, Vittorio, Università di Brescia, Italy
Mescheder, Ulrich, Univ. of Applied Sciences, Furtwangen, Germany

Editor for Eastern Europe

Sachenko, Anatoly, Ternopil National Economic University, Ukraine

Editors for North America

Katz, Evgeny, Clarkson University, USA
Datskos, Panos G., Oak Ridge National Laboratory, USA
Fabien, J. Josse, Marquette University, USA

Editor for Africa

Maki K., Habib, American University in Cairo, Egypt

Editors South America

Costa-Felix, Rodrigo, Inmetro, Brazil
Walsole de Reca, Noemi Elisabeth, CINSO-CITEDEF
UNIDEF (MINDEF-CONICET), Argentina

Editors for Asia

Ohyama, Shinji, Tokyo Institute of Technology, Japan
Zhengbing, Hu, Huazhong Univ. of Science and Technol., China
Li, Gongfa, Wuhan Univ. of Science and Technology, China

Editor for Asia-Pacific

Mukhopadhyay, Subhas, Massey University, New Zealand

International Advisory Board

Abdul Rahim, Ruzairi, Universiti Teknologi, Malaysia
Abramchuk, George, Measur. Tech. & Advanced Applications, Canada
Aluri, Geetha S., Globalfoundries, USA
Ascoli, Giorgio, George Mason University, USA
Atalay, Selcuk, Inonu University, Turkey
Atghiaee, Ahmad, University of Tehran, Iran
Augutis, Vygtantas, Kaunas University of Technology, Lithuania
Ayesh, Aladdin, De Montfort University, UK
Baliga, Shankar, B., Laser Components DG, Inc., USA
Barlingay, Ravindra, Larsen & Toubro - Technology Services, India
Basu, Sukumar, Jadavpur University, India
Bousbia-Salah, Mounir, University of Annaba, Algeria
Bouvet, Marcel, University of Burgundy, France
Campanella, Luigi, University La Sapienza, Italy
Carvalho, Vitor, Minho University, Portugal
Changhai, Ru, Harbin Engineering University, China
Chen, Wei, Hefei University of Technology, China
Cheng-Ta, Chiang, National Chia-Yi University, Taiwan
Cherstvy, Andrey, University of Potsdam, Germany
Chung, Wen-Yaw, Chung Yuan Christian University, Taiwan
Cortes, Camilo A., Universidad Nacional de Colombia, Colombia
D'Amico, Arnaldo, Università di Tor Vergata, Italy
De Stefano, Luca, Institute for Microelectronics and Microsystem, Italy
Ding, Jianning, Changzhou University, China
Djordjević, Alexander, City University of Hong Kong, Hong Kong
Donato, Nicola, University of Messina, Italy
Dong, Feng, Tianjin University, China
Erkmen, Aydan M., Middle East Technical University, Turkey
Fezari, Mohamed, Badji Mokhtar Annaba University, Algeria
Gaura, Elena, Coventry University, UK
Gole, James, Georgia Institute of Technology, USA
Gong, Hao, National University of Singapore, Singapore
Gonzalez de la Rosa, Juan Jose, University of Cadiz, Spain
Goswami, Amarjyoti, Kaziranga University, India
Guillet, Bruno, University of Caen, France
Hadjiloucas, Sillas, The University of Reading, UK
Hao, Shiyang, Michigan State University, USA
Hui, David, University of New Orleans, USA
Jaffrezic-Renault, Nicole, Claude Bernard University Lyon 1, France
Jamil, Mohammad, Qatar University, Qatar
Kaniusas, Eugenijus, Vienna University of Technology, Austria
Kim, Min Young, Kyungpook National University, Korea
Kumar, Arun, University of Delaware, USA
Lay-Ekuakille, Aime, University of Lecce, Italy
Li, Fengyuan, HARMAN International, USA
Li, Jingsong, Anhui University, China
Li, Si, GE Global Research Center, USA
Lin, Paul, Cleveland State University, USA
Liu, Aihua, Chinese Academy of Sciences, China
Liu, Chenglian, Long Yan University, China
Liu, Fei, City College of New York, USA
Mahadi, Muhammad, University Tun Hussein Onn Malaysia, Malaysia
Mansor, Muhammad Naufal, University Malaysia Perlis, Malaysia

Marquez, Alfredo, Centro de Investigacion en Materiales Avanzados, Mexico
Mishra, Vivekanand, National Institute of Technology, India
Moghavvemi, Mahmoud, University of Malaya, Malaysia
Morello, Rosario, University "Mediterranea" of Reggio Calabria, Italy
Mulla, Imtiaz Sirajuddin, National Chemical Laboratory, Pune, India
Nabok, Aleksey, Sheffield Hallam University, UK
Neshkova, Milka, Bulgarian Academy of Sciences, Bulgaria
Pal, Jitendra, Carnegie Mellon University, USA
Passaro, Vittorio M. N., Politecnico di Bari, Italy
Patil, Devidas Ramrao, R. L. College, Parola, India
Penza, Michele, ENEA, Italy
Pereira, Jose Miguel, Instituto Politecnico de Seteбал, Portugal
Pillarsetti, Anand, Sensata Technologies Inc, USA
Pogacnik, Lea, University of Ljubljana, Slovenia
Pullini, Daniele, Centro Ricerche FIAT, Italy
Qiu, Liang, Avago Technologies, USA
Reig, Candid, University of Valencia, Spain
Restivo, Maria Teresa, University of Porto, Portugal
Rodríguez Martínez, Angel, Universidad Politécnica de Cataluña, Spain
Sadana, Ajit, University of Mississippi, USA
Sadeghian Marnani, Hamed, TU Delft, The Netherlands
Sapozhnikova, Ksenia, D. I. Mendeleyev Institute for Metrology, Russia
Singhal, Subodh Kumar, National Physical Laboratory, India
Shah, Kriyang, La Trobe University, Australia
Shi, Wendian, California Institute of Technology, USA
Shmaliy, Yuriy, Guanajuato University, Mexico
Song, Xu, An Yang Normal University, China
Srivastava, Arvind K., Systron Donner Inertial, USA
Stefanescu, Dan Mihai, Romanian Measurement Society, Romania
Sumriddetchkajorn, Sarun, Nat. Electr. & Comp. Tech. Center, Thailand
Sun, Zhiqiang, Central South University, China
Sysoev, Victor, Saratov State Technical University, Russia
Thirunavukkarasu, I., Manipal University Karnataka, India
Thomas, Sadiq, Heriot Watt University, Edinburgh, UK
Tian, Lei, Xidian University, China
Tianxing, Chu, Research Center for Surveying & Mapping, Beijing, China
Vanga, Kumar L., ePack, Inc., USA
Vazquez, Carmen, Universidad Carlos III Madrid, Spain
Wang, Jiangping, Xian Shiyou University, China
Wang, Peng, Qualcomm Technologies, USA
Wang, Zongbo, University of Kansas, USA
Xu, Han, Measurement Specialties, Inc., USA
Xu, Weihe, Brookhaven National Lab, USA
Xue, Ning, Agiltron, Inc., USA
Yang, Dongfang, National Research Council, Canada
Yang, Shuang-Hua, Loughborough University, UK
Yaping Dan, Harvard University, USA
Yue, Xiao-Guang, Shanxi University of Chinese Traditional Medicine, China
Xiao-Guang, Yue, Wuhan University of Technology, China
Zakaria, Zulkarnay, University Malaysia Perlis, Malaysia
Zhang, Weiping, Shanghai Jiao Tong University, China
Zhang, Wenming, Shanghai Jiao Tong University, China
Zhang, Yudong, Nanjing Normal University China

Contents

Volume 252
Issue 5
October 2021

www.sensorsportal.com

ISSN 2306-8515
e-ISSN 1726-5479

Research Articles

Dynamic Verification of a Static Calibrated 3-Axis Accelerometer Using a Slider-Crank Mechanism and the Method of Variable Projection <i>M. Rollett, E. Theussl, E. Lang and P. O'Leary</i>	1
Digital Magnetometer Based on Giant Magneto Impedance Effect: a Feasibility Study <i>Papa Silly Traore and Mamaye Inès Correa</i>	12
Modified Ultrasonic Liquid Level Transducer Using Wave Intensity as the Informative Parameter <i>Haraprasad Mandal, Madhuchhanda Mitra and Satish Chandra Bera</i>	19
Systematic Failure Detection and Correction in Environmental Monitoring Systems <i>Gonçalo de Jesus, Anabela Oliveira and António Casimiro</i>	28
Simulation and Measurement of Comfort Related Microclimate <i>Michael Kurz, Christoph Russ and Bernhard Kurz</i>	35
Deep Learning-Based Detection of Abnormal Respiration Based on Abdominal 3D Shape Dynamically Measured by Moiré Topography <i>Yuki Mochizuki and Norio Tagawa</i>	42
Regressing Relative Fine-Grained Change for Sub-Groups in Unreliable Heterogeneous Data Through Deep Multi-Task Metric Learning <i>Niall O' Mahony, Sean Campbell, Lenka Krpalkova, Joseph Walsh and Daniel Riordan</i> ..	50
Home Monitoring of Vital Parameters Using Intelligent Sensor and Storage Networks <i>Ulrich H. P. Fischer, Jens-Uwe Just and Fabian Theuerkauf</i>	58
Turbo Coded Single User Massive MIMO <i>K. Vasudevan, A. Phani Kumar Reddy, Gyanesh Kumar Pathak and Mahmoud Albreem</i>	65

Authors are encouraged to submit article in MS Word (doc) and Acrobat (pdf) formats
by e-mail: editor@sensorsportal.com. Please visit journal's webpage with preparation instructions:
<http://www.sensorsportal.com/HTML/DIGEST/Submission.htm>

Dynamic Verification of a Static Calibrated 3-Axis Accelerometer Using a Slider-Crank Mechanism and the Method of Variable Projection

M. ROLLETT, E. THEUSSL, E. LANG and P. O'LEARY

University of Leoben, Chair of Automation, Peter Tunner Strasse 25, 8700 Leoben, Austria

Tel.: +43 3842 402 5301, fax: +43 3842 402 5302

E-mail: automation@unileoben.ac.at

Received: 30 July 2021 /Accepted: 28 September 2021 /Published: 31 October 2021

Abstract: This paper presents a new method of calibration for a 3-axis MEMS accelerometer and its dynamic verification. The new combination of calibration and dynamic verification ensures the correct calculation of the displacement and velocity from the measured accelerations of systems with significant motion. The nine parameters required for complete calibration of the accelerometer are obtained using the non-linear optimisation, whereby the method of variable projection (VPM) is used to implement the optimisation. The dynamic verification is performed on a test bed corresponding to a slider-crank mechanism. Principal component analysis is used to correct for possible rotations of the sensor, relative to the linear motion. The results presented in this paper demonstrate the correct functionality of the calibration and verification procedures.

Keywords: Calibration, Variable projection method, Non-linear optimisation, Dynamic verification, MEMS accelerometer.

1. Introduction

This article is an extension to the introduced dynamic verification using a slider-crank type test stand of a statically calibrated sensor system based on a MEMS accelerometer [1]. This paper addresses the issue of ensuring that the calibration procedure of 3-axis MEMS accelerometers introduced in [2] yield accurate measurements of dynamic systems with significant motion. The 3-axis accelerometer sensing element is part of a newly developed sensor module providing significant computational power and a wireless interface. The calibration procedure presented in [2] calibrates for misalignments of the sensing element within the sensor module as well as for gain and offset. This is important with equipment, where there is significant motion of relatively low frequency (1Hz – 12Hz). In numerous industrial applications it is necessary to compute accurate

displacements and velocities from the measured acceleration, e.g., a rod and piston type system [3] or vibrational sieves [2]. Consequently, it is necessary to verify that the accelerometers correctly measure the dominant signal component and its harmonics; for this reason, this article investigates whether or not a static calibration is sufficient in dynamic low frequency application of significant motion by verification using a slider-crank type test stand. However, a piston type system has a non-linear relationship between the rotation that creates the significant motion and the acceleration of the slider itself.

In this article we present two methods to verify the sensor calibration:

1. A frequency response test using a model for the acceleration of the slider-crank mechanism serving as a reference.

2. A geometrically constraint method using the constant radius of the crank serving as reference for a

piston model. This allows to compare the model radius and the recalculated radius from the determined acceleration via integration.

Most commonly, 3-axis MEMS sensors are statically calibrated using multiple orientations [4, 5]; however, dynamic verification is rarely performed. D'Emilia, *et al.* [6] present a dynamic calibration. Although, there is a linear relationship between the initiating motion and the measured acceleration. This case does not require the verification of the correct measurement of additional harmonics. This contrasts with the test-stand presented in this work which generates additional harmonics.

The main contributions of this paper are:

1. A calibration process, which uses the method of variable projection [7, 8] to implement the calculation of the calibration coefficients. This ensures a more precise calibration, while being numerically stable and efficient.
2. A test stand corresponding to a slider-crank system - a mechanism commonly used in industry - for verifying the static calibration. This creates a non-linear relationship between the initiating rotation and the ensuing accelerations.
3. Verification calculations, which show that the calibration is accurate within the error bounds of the mechanical test stand.

2. Static Calibration

In this article a static calibration of a 3-axis MEMS accelerometer is presented by modelling the most significant sources of errors.

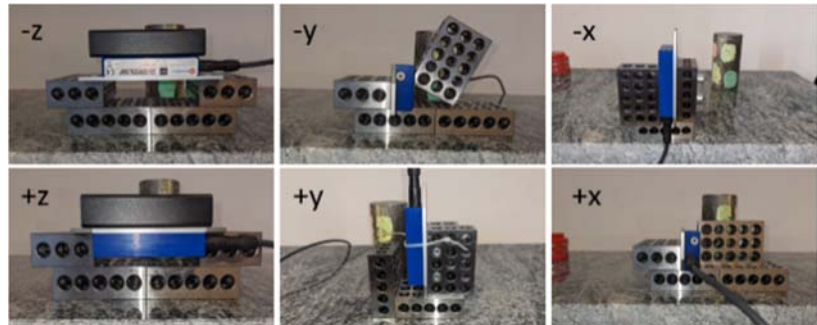
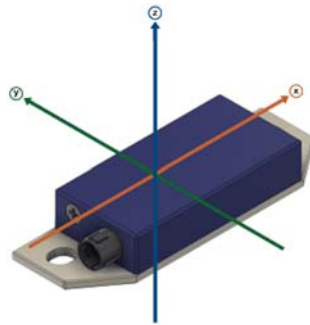


Fig. 2. Left: The orientation of the acceleration sensing element axes within in the module wrt. the aluminium base plate. **Right:** 6 orthogonal orientation positions for calibration of the 3-axis accelerometer. At each orientation an axis (labelled as: -z, -y, -x, +z, +y, +x) pointed towards the earth gravitational centre. As surface, a levelled Granit stone is used. A precision water level was used to level the surface. The stone was encapsulated from the vibrating environment with speaker dampers. 1-2-3 blocks were used to hold the sensor in the necessary positions.

2.1. Calibration Model

In this article a 10 degree-of-freedom (DOF) sensor is used; 3-axis acceleration, 3-axis gyroscope, 3-axis magnetic field and temperature. Nevertheless, this article is about calibration of the 3-axis acceleration sensor; A calibration model for this

The first source of measurement errors considered in the presented method is due to assembly tolerances and inaccuracies of the sensing element. These occur during the placement of the MEMS-element on the sensor systems printed circuit board (PCB), see Fig. 1.

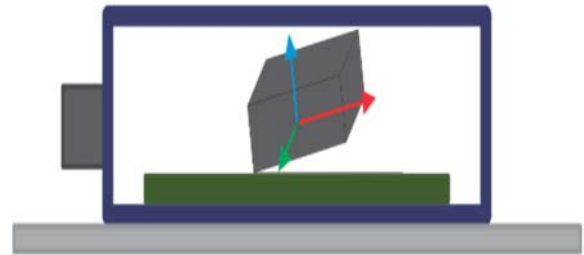


Fig. 1. Orientation of the sensor chip within the module housing. Due to assembly tolerances the MEMS-chip can be rotated wrt. the module housing axes.

In more detail, the exact source of the error is a misalignment of the sensing axes within a sensor module and the fixing surface of the sensor modules housing, see Fig. 2 (left). This step of the calibration determines a coordinate transformation between the axes of the sensing element within the sensor housing and the contact surface of the sensor module itself. This is important since the contact surface defines the coordinate system for the acquired acceleration data wrt. machine where the sensor is mounted.

In addition, a bias (offset) and gain are used to model errors which occur due to tolerances of electronic circuit and sensing element tolerances.

sensor system was already introduced in [1, 2]. For the sake of completeness, it is added in this article.

For the 3-axis accelerometer in Fig. 2, a 9 DOF model has been chosen to model three independent offsets (bias) errors, three gains and three angles for each axis respectively.

With regard to the calibration model, a measurement $\mathbf{m}$ is defined as

$$\mathbf{m} = \begin{bmatrix} x_m \\ y_m \\ z_m \end{bmatrix}, \quad (1)$$

consisting of individual measurement samples in the x-, y- and z-axis. The calibrated measurements

$$\mathbf{m}_c = \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix}, \quad (2)$$

are calculated by applying the calibration model defined as

$$\mathbf{m}_c = \mathbf{G}\mathbf{R}_m\mathbf{m} + \mathbf{c} \quad (3)$$

The misalignment of the sensor is modelled as a rotation matrix $\mathbf{R}(\phi_x, \phi_y, \phi_z)$ defined as

$$\mathbf{R}(\phi_x, \phi_y, \phi_z) = \mathbf{R}_z(\phi_z)\mathbf{R}_y(\phi_y)\mathbf{R}_x(\phi_x), \quad (4)$$

which is composed of three rotation matrices in the 3D space. The individual rotation matrices considering three angles ϕ_x, ϕ_y, ϕ_z , are calculated by

$$\mathbf{R}_z(\phi_z) = \begin{bmatrix} \cos\phi_z & -\sin\phi_z & 0 \\ \sin\phi_z & \cos\phi_z & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad (5)$$

$$\mathbf{R}_y(\phi_y) = \begin{bmatrix} \cos\phi_y & 0 & \sin\phi_y \\ 0 & 1 & 0 \\ -\sin\phi_y & 0 & \cos\phi_y \end{bmatrix} \text{ and} \quad (6)$$

$$\mathbf{R}_x(\phi_x) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi_x & -\sin\phi_x \\ 0 & \sin\phi_x & \cos\phi_x \end{bmatrix} \quad (7)$$

The goal of the rotation is, to ensure, that the orientation of the MEMS sensor axis (Fig. 1) is aligned with the aluminium mounting base coordinate axes (Fig. 2, left) of the sensor housing. This then defines the aluminium base as the reference coordinate system of the sensor module. Due to manufacturing tolerances of electronic parts, the data of such a sensor system is also affected by a gain $\mathbf{G}$ and an offset $\mathbf{c}$ in each axis. Since the gain is independent for each axis, it can be defined as a 3×3 diagonal matrix,

$$\mathbf{G} = \begin{bmatrix} g_x & 0 & 0 \\ 0 & g_y & 0 \\ 0 & 0 & g_z \end{bmatrix} \quad (8)$$

The offset is defined as a 3×1 vector,

$$\mathbf{c} = \begin{bmatrix} c_x \\ c_y \\ c_z \end{bmatrix} \quad (9)$$

To summarize the introduced parameters being calculated for calibration are the rotation in each axis ϕ_x, ϕ_y , and ϕ_z , as well as the parameters for the gain g_x, g_y and g_z and the offset c_x, c_y and c_z .

To make it clear that this non-linear problem can be separated into a linear and a non-linear problem Eqn. (3) can be reformulated by augmentation.

Augmenting a measurement $\mathbf{m}$ yields a vector $\mathbf{m}_a$ defined as,

$$\mathbf{m}_a = \begin{bmatrix} x_m \\ y_m \\ z_m \\ 1 \end{bmatrix} \quad (10)$$

In the same manner, the rotation matrices are augmented to satisfy the dimensions. It is defined by the augmented rotation matrix $\mathbf{R}_a$ as a 3×4 matrix

$$\begin{aligned} \mathbf{R}_a(\phi_x, \phi_y, \phi_z) &= \\ &= \begin{bmatrix} \mathbf{R}_z(\phi_z) & \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{R}_y(\phi_y) & \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mathbf{R}_x(\phi_x) & \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\ 0 & 0 & 0 & 1 \end{bmatrix} \end{aligned} \quad (11)$$

The augmented calibration model can now be written as,

$$\mathbf{m}_c = \underbrace{\begin{bmatrix} g_x & 0 & 0 & c_x \\ 0 & g_y & 0 & c_y \\ 0 & 0 & g_z & c_z \end{bmatrix}}_{\text{linear}} \underbrace{\begin{bmatrix} \mathbf{R}_a(\phi_x, \phi_y, \phi_z) \\ 1 \end{bmatrix}}_{\text{non-linear in } \phi} \begin{bmatrix} x_m \\ y_m \\ z_m \\ 1 \end{bmatrix} \quad (12)$$

The solution to calculate a calibrated measurement has now become a formulation of separable variables [9], since the problem is split-up into a linear and non-linear portion. First, the non-linear part is applied on the augmented measurements $\mathbf{m}_a$ by a rotation $\mathbf{R}_a(\phi_x, \phi_y, \phi_z)$, where ϕ_x, ϕ_y , and ϕ_z are common to all three axes. Second, the linear part contains now only the linear parameters in $\mathbf{G}$ and $\mathbf{c}$ of each axis respectively.

By continuing from Eqn. (12) the calibration model can be further simplified for a computationally optimized solution. Applying the rotation

$R_a(\phi_x, \phi_y, \phi_z)$ on $\mathbf{m}_a$ yields the rotated measurements $\mathbf{m}_r$:

$$\mathbf{m}_r = \begin{bmatrix} x_r \\ y_r \\ z_r \\ 1 \end{bmatrix} = \begin{bmatrix} R_a(\phi_x, \phi_y, \phi_z) \end{bmatrix} \begin{bmatrix} x_m \\ y_m \\ z_m \\ 1 \end{bmatrix} \quad (13)$$

Substitute Eqn. (13) in Eqn. (12) yields the forward problem

$$\mathbf{m}_c = \begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = \begin{bmatrix} g_x & 0 & 0 & c_x \\ 0 & g_y & 0 & c_y \\ 0 & 0 & g_z & c_z \end{bmatrix} \begin{bmatrix} x_r \\ y_r \\ z_r \\ 1 \end{bmatrix}, \quad (14)$$

which has now become a purely linear problem for a stationary angle ϕ_x , ϕ_y and ϕ_z . In order to calculate calibrated measurements, the equation can be reformulated according to Graßmann duality [10], which results into

$$\begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = \begin{bmatrix} x_r & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & y_r & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & z_r & 1 \end{bmatrix} \begin{bmatrix} g_x \\ c_x \\ g_y \\ c_y \\ g_z \\ c_z \end{bmatrix} \quad (15)$$

Further, as the structure of this matrix equation suggests, the unknown parameters are independent from each other. This allows to extract separate equations for x_c , y_c and z_c as follows

$$x_c = [x_r \quad 1] \begin{bmatrix} g_x \\ c_x \end{bmatrix}, \quad (16)$$

$$y_c = [y_r \quad 1] \begin{bmatrix} g_y \\ c_y \end{bmatrix}, \quad (17)$$

$$z_c = [z_r \quad 1] \begin{bmatrix} g_z \\ c_z \end{bmatrix} \quad (18)$$

The extraction allows a numerically efficient way of solving for calibrated measurements, since the nine-dimensional problem is reduced to three equations in two dimensions.

3. Determination of the Calibration Parameters

A static calibration method was used to determine the unknown parameters. However, within the calibration process, in each measurement, the sensor aluminium base was orientated with a different lateral face towards the centre of gravity. This ensures all lateral faces have been pointed once towards the centre of gravity. It results into six independent measurements, each yielding the respective acceleration for the x-, y- and z- axis. The right-hand

side of Fig. 2 shows the orientation of the sensor during the static measurements for the calibration. The letter in each sub-photograph states which axis pointed towards the centre of gravity while acquiring the data.

3.1. Defining the Cost Function

The calibration model presented in Eqn. (3) is the basis to formulate a model $\mathbf{A}$ considering all six measurements from the static calibration, yielding

$$\mathbf{A} = \mathbf{GRM} + \mathbf{C}, \quad (19)$$

where $\mathbf{M}$ is defined by the mean values $\bar{x}_{m,1} \dots \bar{x}_{m,6}$, $\bar{y}_{m,1} \dots \bar{y}_{m,6}$ and $\bar{z}_{m,1} \dots \bar{z}_{m,6}$ from each measurement of n samples of each axis. This is summarized in a 3×6 matrix $\mathbf{M}$:

Data merged according to the sensor's orientation in Fig. 2:

$$\mathbf{M} = \begin{bmatrix} \bar{x}_{m,1} & \bar{x}_{m,2} & \bar{x}_{m,3} & \bar{x}_{m,4} & \bar{x}_{m,5} & \bar{x}_{m,6} \\ \bar{y}_{m,1} & \bar{y}_{m,2} & \bar{y}_{m,3} & \bar{y}_{m,4} & \bar{y}_{m,5} & \bar{y}_{m,6} \\ \bar{z}_{m,1} & \bar{z}_{m,2} & \bar{z}_{m,3} & \bar{z}_{m,4} & \bar{z}_{m,5} & \bar{z}_{m,6} \end{bmatrix} \quad (20)$$

The matrix $\mathbf{A}$, defines a 3×6 reference matrix which specifies the expected acceleration due to the gravitational force for each orientation respectively, defined by $g = 9.81 \frac{m}{s^2}$:

$$\mathbf{A} = \begin{bmatrix} -g & g & 0 & 0 & 0 & 0 \\ 0 & 0 & -g & g & 0 & 0 \\ 0 & 0 & 0 & 0 & -g & g \end{bmatrix} \quad (21)$$

The signs of the entries in $\mathbf{A}$ correspond to the orientations of the lateral faces of the sensor shown in Fig. 2 and directly relates to the definitions in $\mathbf{M}$ (-x and x, -y and y as well as -z and z).

The offset matrix $\mathbf{C}$ is defined as a 3×6 matrix:

$$\mathbf{C} = \begin{bmatrix} c_x & \dots & c_x \\ c_y & \dots & c_y \\ c_z & \dots & c_z \end{bmatrix} \quad (22)$$

Once the calibration parameters have been determined, a corrected set of measurements $\mathbf{A}_r$ can then be calculated by,

$$\mathbf{A}_r = \mathbf{GRM} + \mathbf{C} \quad (23)$$

The cost function for the non-linear problem can now be defined as the Frobenius-norm from the residual between the ideal values in $\mathbf{A}$ and the corrected measurements in $\mathbf{A}_r$

$$\epsilon(\phi_x, \phi_y, \phi_z) = \min \|\mathbf{A}_r - \mathbf{A}\|_F \quad (24)$$

For the computation of the calibration parameters in $\mathbf{G}$, $\mathbf{C}$ and $\mathbf{R}$, Eqn. (23), Eqn. (24) is later split into a

linear and non-linear part by applying the method of separable variables.

3.2. Computation of the Calibration Parameters

To yield the nine calibration parameters: the rotation in each axis ϕ_x, ϕ_y, ϕ_z ; the gain in each axis g_x, g_y, g_z and the offset in each axis c_x, c_y, c_z , the method of separable variables is applied. Considering the non-linear portion due to the rotation $R(\phi_x, \phi_y, \phi_z)$ for a static angle ϕ_x, ϕ_y , and ϕ_z applied on the measurement $\mathbf{M}$, yields

$$\mathbf{M}_r = \mathbf{R}(\phi_x, \phi_y, \phi_z) \mathbf{M} \quad (25)$$

To solve for the measurements $\mathbf{M}_r$, the model in Eqn. (19) is reformulated as

$$\mathbf{A} = \mathbf{G}\mathbf{M}_r + \mathbf{C} \quad (26)$$

Subtracting $\mathbf{C}$ from $\mathbf{A}$ yields

$$\mathbf{A} - \mathbf{C} = \mathbf{G}\mathbf{M}_r \quad (27)$$

Eqn. (27) is a set of equations. To determine the linear calibration parameters, the equations in (27) must be considered individually. In the following, the way to solve for the parameters in the x-axis is exemplary shown. The steps from equation Eqn. (28) to Eqn. (38) are identical for the x-, y-axis and z-axis.

Considering the equation for the x-axis, a rotated measurements $\mathbf{m}_{x,r}$ extracted from $\mathbf{M}_r$ yields,

$$\mathbf{m}_{x,r} = [\bar{x}_{m,r,1} \quad \bar{x}_{m,r,2} \quad \cdots \quad \bar{x}_{m,r,6}]^T \quad (28)$$

From $\mathbf{A}$, an ideal vector $\mathbf{a}_x$ is extracted, such that

$$\mathbf{a}_x = [-g \quad g \quad 0 \quad 0 \quad 0 \quad 0]^T, \quad (29)$$

and from $\mathbf{C}$ an offset vector $\mathbf{c}_x$ of the dimension 6×1 ,

$$\mathbf{c}_x = [c_x \quad c_x \quad \cdots \quad c_x]^T \quad (30)$$

After performing the multiplication $\mathbf{G}\mathbf{M}_r$ the following equation can be formulated corresponding to Eqn. (27),

$$\mathbf{a}_x - \mathbf{c}_x = g_x \mathbf{m}_{x,r} \quad (31)$$

Dividing by the scalar value for the gain g_x yields

$$\frac{1}{g_x} \mathbf{a}_x - \frac{1}{g_x} \mathbf{c}_x = \mathbf{m}_{x,r} \quad (32)$$

Eqn. (32) can be reformulated into its matrix-vector form for each axis respectively which yields the model equation

$$\mathbf{m}_{x,r} = \begin{bmatrix} \bar{x}_{m,r,1} \\ \bar{x}_{m,r,2} \\ \bar{x}_{m,r,3} \\ \bar{x}_{m,r,4} \\ \bar{x}_{m,r,5} \\ \bar{x}_{m,r,6} \end{bmatrix} = \begin{bmatrix} -g & 1 \\ g & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \frac{1}{g_i} \\ -\frac{1}{g_i} c_i \end{bmatrix} \quad (33)$$

Defining the basis matrix $\mathbf{B}_x$ as

$$\mathbf{B}_x = \begin{bmatrix} -g & 1 \\ g & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix} \quad (34)$$

and the coefficient vector α_x as

$$\alpha_x = \begin{bmatrix} \frac{1}{g_x} & -\frac{1}{g_x} c_x \end{bmatrix}^T \quad (35)$$

yields,

$$\mathbf{m}_{x,r} = \mathbf{B}_x \alpha_x \quad (36)$$

Solving the linear system for the calibration parameters in α_x yields,

$$\alpha_x = \mathbf{B}_x^+ \mathbf{m}_{x,r} \quad (37)$$

Here $\mathbf{B}_x^+$ denotes the Moore-Penrose pseudo inverse of $\mathbf{B}_x$.

For the desired coefficients α_x , given $\mathbf{m}_{x,r}$, the minimisation of the cost function wrt. ϕ yields

$$\epsilon_x(\phi) = \left\| \mathbf{a}_{x,r} - \mathbf{B}_x \alpha_x \right\|_2^2 \quad (38)$$

After computing the coefficients for all axes, the coefficients for the gain and offset can be collated in the gain matrix $\mathbf{G}$ and the offset matrix $\mathbf{C}$.

3.3. Implementation

In the following the MATLAB m-code is presented which shows the implementation of the above-described algorithm. Listing 1 shows the cost-function which is being minimized. Consequently, given a stationary point for ϕ_x, ϕ_y and ϕ_z , allows to independently solve for the linear parameters in $\mathbf{G}$ and $\mathbf{C}$.

```

1 function cost =
2 costCal(params,M,A)
3 %% Extract the parameters
4 xPhi = params(1);
5 yPhi = params(2);
6 zPhi = params(3);
7 % Rotate the measurement data M
8 R = rotz(zPhi) * roty(yPhi) *
9 rotx(xPhi);
10 Mr = R*M;
11 %
12 % Solve the linear portion
13 G = zeros(3);
14 c = zeros(3,1);
15 for k = 1:3
16     ak = A(k,:);
17     D = [ak, ones(size(ak))];
18     mr = Mr(k,:);
19     %
20     cfs = D \ mr;
21     %
22     G(k,k) = 1/cfs(1);
23     c(k) = - cfs(2)/cfs(1);
24 end
25 % Compute the corrected
26 measurements
27 Ar = (G * Mr + repmat(c,1,6));
28 % Compute the cost
29 E = A - Ar;
30 cost = norm(E, 'fro')/sqrt(18);

```

Listing 1 M-code for the cost function for solving the linear portion of the calibration model for a 3-axis accelerometer.

The code presented in Listing 1 is wrapped by a non-linear solver to minimize the cost function wrt. The rotation angles ϕ_x, ϕ_y, ϕ_z as shown in Listing 2:

```

1 fun = @(phis)costCal(phis, M, A);
2 phis = fminsearch(fun, phisInit);

```

Listing 2 M-code wrapping the linear portion of Listing 1 by a non-linear solver.

4. Dynamic Verification

Most industrial application require the sensor to work in a dynamic setup, where the acceleration change over time. This contrasts with the presented simplified static calibration procedure. Thus, it is necessary to verify the new calibration method for measurements of dynamic motions. Therefore, a thoroughly verification is presented using a frequency response test for two independent calibrated sensors of significant motion. The measurement data is recorded at different acceleration frequencies. The method of identifying a periodic signal using VPM introduced in [8] and FFT [11] is used to determine the dominant acceleration amplitudes of each tested frequency and subsequently compared to a reference acceleration computed from the slider-crank model of the test stand.

4.1. Test System

A small test stand, based on a slider-crank mechanism was built, to generate a non-linear relationship between the rotational motion of an electronic motor and a linear motion of a piston, see Fig. 3. The nature of such a mechanical drive system has a defined acceleration model which allows to determine the exact expected acceleration at a certain rotational frequency. A speed controller enables the control of the rotational speed of a 12 V DC motor. A cylindric support holds the slider in lateral position serving as a linear support. The sensor module is fixed on the platform such that it can be exposed by the linear motion in only one direction.

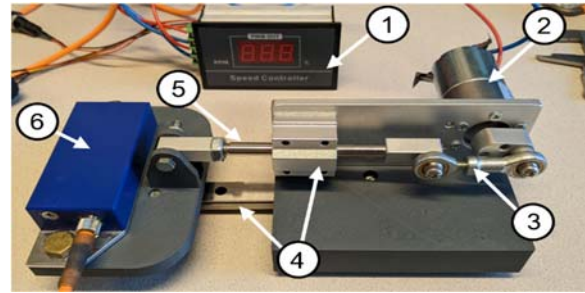


Fig. 3. Test stand. 1: speed controller; 2: motor; 3: connecting rod; 4: supports; 5: slider; 6: sensor module including a 3-axis accelerometer.

4.2. Model of the Test System

The equation for the acceleration of the slider-crank mechanism $a(\varphi)$ is

$$a(\varphi) = r\omega^2 \left(\cos\varphi + \lambda \frac{\cos 2\varphi + \lambda^2 \sin^4 \varphi}{\sqrt{(1 - \lambda^2 \sin^2 \varphi)^3}} \right) \quad (39)$$

It describes the acceleration of the slider depending on the angle φ and the geometry of the test rig given by the connecting rod to crank ratio λ [3]. In Fig. 4 a schematic sketch of a slider-crank mechanism can be seen. The angular position φ is defined as 0° when the piston is at the upper dead center (UDC) and is increasing when rotating clockwise up to 180° until it reaches the outer dead center (ODC). The cycle then reaches 360° which corresponds to the 0° starting position. The connecting rod ratio $\lambda = \frac{r}{l}$ is defined as the relationship between the length l of the connecting rod and the radius r of the crank, see Fig. 4. The ratio affects the behaviour of the piston's movement along its support.

4.3. Data Acquisition

Two sensor modules were tested using different acceleration sensing elements: The MPU-9250 and the ICM-20948. The data from the test run was recorded

with a sampling frequency of 2048 Hz for one second resulting in $n = 2048$ measurements in each axis. Both sensors have been parametrized at a sensitivity of 8 g. The introduced calibration algorithm has been directly implemented in the sensor module, hence the data acquired from the sensor was already calibrated.

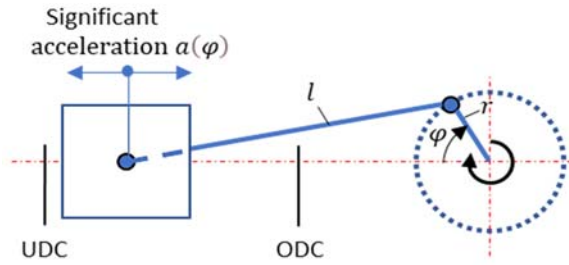


Fig. 4. Top: Enlarged visualization of the slider-crank mechanism of the test stand. **Bottom:** Principal sketch of a slider-crank mechanism. The definition of the connecting rod length l and the crank with the radius r are defined and yields the ratio $\lambda = \frac{r}{l}$. The upper dead centre (UDC) is defined when the drive has reached a ϕ of 0° , the outer dead centre (ODC) is reached at a ϕ of 180° .

The motors revolutions per minutes were parametrized using a speed controller from 0 % up to 100 %, whereby 100 % correspond theoretically to 800 rpm. The speed controller's parameters are used as a reference for ω in the model. Thus, the true slider-crank mechanisms revolutions per minute are calculated using the periodic acceleration signal and a Fourier transformation. However, it was observed that a stable movement of the acceleration sensor on the test stand required the speed controller parametrized at greater 20 %. This corresponds to a minimum experiment frequency of $f_{min} = 2.49 \text{ Hz}$.

4.4. Frequency Determination Using the Variable Projection Method

A measurement of a periodic signal usually is not a perfectly periodic. When applying the Fast Fourier transformation (FFT) on such a signal, the resulting transformation will be subject to a Gibbs error [12]. The Gibbs error results in a falsified spread of the signals energy in the frequency domain of the Fourier transform. Although, it can be reduced by different filtering methods. A very common method is to apply a window to the original signal or smoothing of the raw data. Also trimming the data to a fully periodic signal by finding the zero crossings is a common technique for reducing the Gibbs error.

A more sufficient method of frequency determination is introduced in [8], using the variable projection method [13, 14]. The method is based on a four-parameter sine wave model and is defined in the IEEE standards [15]. The advantage of this method is to determine the dominant frequency and the corresponding amplitude from a signal without being subject to Gibbs errors. It is characterized by a model being a linear combination of nonlinear functions.

The four-parameter sine wave model can be defined as algebraic formulation,

$$\mathbf{y}_m = d + a_c \cos(\omega \mathbf{t}) + a_s \sin(\omega \mathbf{t}) \quad (40)$$

Here $\mathbf{y}_m$ defines the model for a measurement $\mathbf{y} = [y_1, \dots, y_n]^T$ performed at the times $\mathbf{t} = [t_1, \dots, t_n]$, where n is the number of samples recorded in a measurement. The coefficients of the model $\mathbf{y}_m$ in Eqn. (40) are d for the direct component (DC) and the amplitudes a_c and a_s for the cosine and sine components respectively. The frequency is defined as ω for both, sine and cosine components of the model. To transform Eqn. (40) into a linear formulation, the basis-vectors $\mathbf{b}_1$ to $\mathbf{b}_3$ are defined as

$$\mathbf{b}_1 \triangleq \mathbf{1} \quad (41)$$

$$\mathbf{b}_2(\omega) \triangleq \cos(\omega \mathbf{t}) \quad (42)$$

$$\mathbf{b}_3(\omega) \triangleq \sin(\omega \mathbf{t}) \quad (43)$$

The basis vectors are now used to formulate the design matrix $\mathbf{D}$ as a function of ω ,

$$\mathbf{D}(\omega) = [\mathbf{b}_1 \quad \mathbf{b}_2(\omega) \quad \mathbf{b}_3(\omega)] \quad (44)$$

The coefficients $\boldsymbol{\gamma}$ can be defined in a 3×1 vector

$$\boldsymbol{\gamma} = [d \quad a_c \quad a_s]^T. \quad (45)$$

Above definitions lead to the matrix vector equation for the model

$$\mathbf{y}_m = \mathbf{D}(\omega) \boldsymbol{\gamma} \quad (46)$$

and equals the algebraic formulation in Eqn. (40). For a given stationary ω , a least squares estimate for $\boldsymbol{\gamma}$ can now be obtained by calculating the inverse

$$\boldsymbol{\gamma} = \mathbf{D}^+(\omega) \mathbf{y}_m, \quad (47)$$

where $\mathbf{D}^+(\omega)$ denotes the Moore Penrose pseudo inverse of $\mathbf{D}(\omega)$. Substituting the calculated coefficients from Eqn. (47) into the model equation Eqn. (46) gives the results

$$\mathbf{y}_m = \mathbf{D}(\omega) \mathbf{D}^+(\omega) \mathbf{y}_m \quad (48)$$

The matrix multiplication $\mathbf{P} = \mathbf{D}(\omega) \mathbf{D}^+(\omega)$ is the projection onto the basis functions contained in $\mathbf{D}(\omega)$. The projection varies with ω , hence this is called the

variable projection. The residual $\mathbf{r}$ between the model $\mathbf{y}_m$ and the observed data $\mathbf{y}$ can be computed as,

$$\mathbf{r} = \mathbf{y} - \mathbf{y}_m \quad (49)$$

The cost function $E(\omega)$ is then defined as the sum of the squares of the residual $\mathbf{r}$.

$$E(\omega) = \|\mathbf{r}\|_2^2 \quad (50)$$

Substituting Eqn. (49) yields,

$$E(\omega) = \|\mathbf{y} - \mathbf{D}(\omega)\mathbf{D}^+(\omega)\mathbf{y}\| \quad (51)$$

$$= \|\{\mathbf{I} - \mathbf{D}(\omega)\mathbf{D}^+(\omega)\}\mathbf{y}\| \quad (52)$$

The result given in Eqn. (52) is called the variable projection functional (VPF). The estimation of ω is now a non-linear least squares problem in one variable. Eqn. (52) permits us to explicitly calculate the cost function $E(\omega)$ for a stationary point of ω for a given measurement $\mathbf{y}$.

4.5. Data Processing

Due to the tolerances in the mechanical system of the test stand the sensor's orientation may not be perfectly aligned wrt. to the axis of motion. A principal component analysis (PCA) [16] was applied to the 3-axis acceleration data, to extract the primary axis of motion. Consequently, the first principal component $\mathbf{p}_1$ is representative for the primary acceleration of the motion. It has the dimension $n \times 1$, where n represents the number of samples obtained during the measurement. Within the dynamic verification the method of variable projection requires an initial value for the solver to determine the non-linear parameter ω . This initial value is taken from the FFT-transform's dominant frequency, see Fig. 5. The number of samples in each measurement was $n = 2048$ with a sampling rate $f_s = 2048$ Hz, yielding a theoretically possible frequency resolution of 1 Hz using the FFT. This contrasts with the method of variable projection, where the frequency resolution is not limited by the ratio of f_s / n .

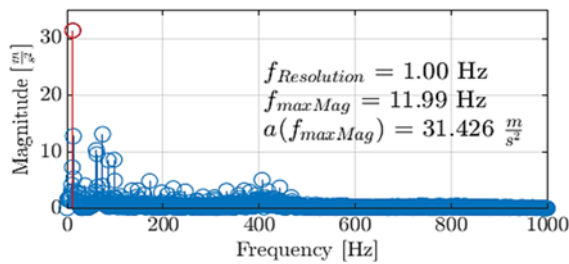


Fig. 5. Graphic representation of the frequency spectrum after a Fast Fourier transformation at the maximum rotational speed. The dominant frequency is highlighted in red and was used as an initial frequency for the VPM.

5. Results

In this section a comparison of determining the frequency and amplitude using FFT and VPM will be shown. This is followed by the results from the frequency response experiment of two examined sensor modules. Based on the calibrated results, a verification of the calibrated acceleration is calculated as

$$r = \iint a(t) dt dt, \quad (53)$$

where $a(t)$ is the denotes the acceleration from the first principal component $\mathbf{p}_1$. The radius r is then compared to the geometry of the slider-crank.

5.1. Comparison FFT and VPM Method

In Fig. 6 the results obtained from the FFT and the VPM approach are visualization for the maximum speed of the test stand. The first principal component $\mathbf{p}_1$ from the calibrated measurements $\mathbf{y}$ is drawn in the figure as a grey line. For comparison, the signal determined via the magnitude and frequency via FFT, denoted as $\mathbf{y}_{FFT}$, is drawn as a blue line. The result from the VPM, given by $\mathbf{y}_m$, is drawn as a red line.

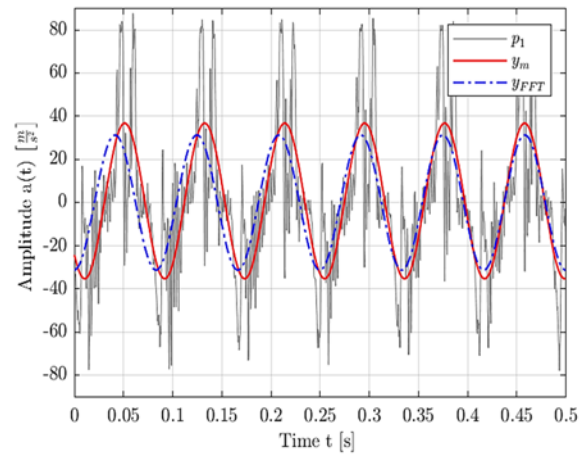


Fig. 6. Data obtained from the sensor after applying PCA is shown in Gray. The VPM result is shown in red and the FFT result in blue. A backlash in the mechanical system can be seen by the two peaks in the principal component. A significant difference in the frequency of the FFT result and the frequency of the principal component can be seen.

The visualization directly shows significant peaks of $\mathbf{p}_1$ at the UDC and ODC of the slider-crank. This can be traced back to a backlash in the mechanical system.

Additionally, a different frequency for the computed signals $\mathbf{y}_{FFT}$ and $\mathbf{y}_m$ is clearly visible. Due to the a limited frequency resolution of the FFT, the estimated peaks of $\mathbf{y}_{FFT}$ are not synchronous with the peaks of $\mathbf{p}_1$.

5.2. Frequency Response Results

A frequency response of a sensor visualizes frequency dependent characteristics of sensors. For this representation, an acceleration measurement of $n = 2048$ samples at $k = 80$ frequencies are obtained. For each frequency k , the maximum

magnitude of acceleration is calculated using VPM. Those results are drawn as red dots Fig. 7. The reference acceleration, determined from the slide-crank mechanism model in Eqn. (39), is plotted as a black line. The maximum and minimum reference acceleration obtained from the radii of the mechanism clearance are visualized as a boundary, indicated as black chain dotted lines.

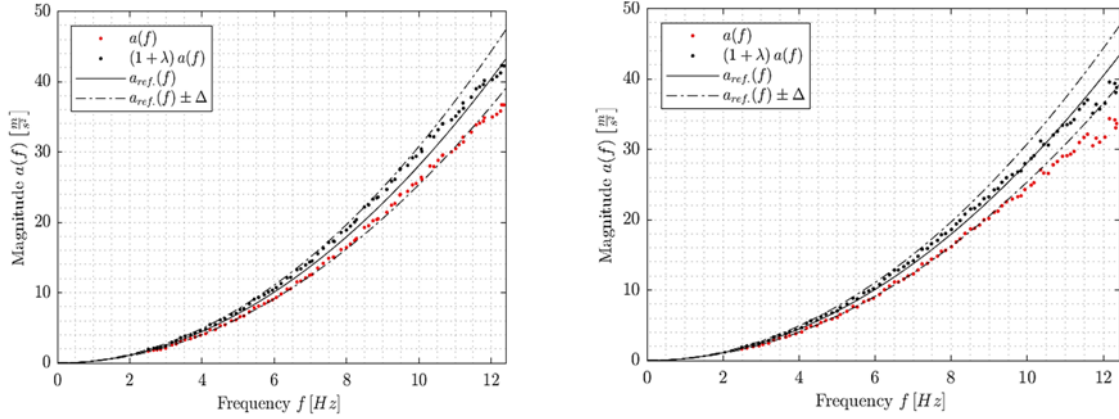


Fig. 7. Frequency response over the speed control range of 20 % to 100 % of the sensor system with the MPU-9250 chip (left) and the ICM20948 (right). The red results are the determined magnitudes from p_1 using the VPM. In black are the VPM results multiplied with the factor of $1 + \lambda$, where $\lambda = 0.1441$ is the trigonometric relationship between the crank and the connecting rod. The reference acceleration is plotted as black line and was determined from the model for a slide-crank drive mechanism. The boundaries $\pm \Delta$ determined from the clearance in the mechanism is plotted as dash dotted line. A dropoff of the acceleration can be seen from approximately 11.5 Hz.

Using the VPM based calibration on two tested sensors, yields accelerations close or slightly beneath the lower boundary $\pm \Delta$ for the theoretical model considering a mechanical clearance. In order to compare the measured acceleration and the theoretical model of the slider-crank mechanism, a gain factor of $1 + \lambda$ has to be added to the calibrated measurements. This comes from the fact, that the VPM method approximates a completely periodic sine wave. However, the reference model in Eqn. (39) delivers at UDC the maximum acceleration $a(\varphi) = r\omega^2(1 + \lambda)$ for $\varphi = 0^\circ$. The sensor module with the ICM-20948 shows slightly better results.

At approximately 11.5 Hz both sensors show a slightly drop off in the acceleration compared to the theoretical model. This is due to the fact that the motor reaches its performance limits wrt. the momentum of the mass of the sensor.

5.3. Displacement Determination

The test stand provides a significant displacement of the sensor. The calibrated measurement results can so additionally be used as verification by calculating the displacement via integration:

$$r = \iint (1 + \lambda)a(f)\cos(\omega t)dt dt \quad (54)$$

Fig. 8 shows the reference displacement r_{cg} calculated by,

$$r_{cg} = \frac{ODC_{max} - UDC_{min}}{4} + \frac{ODC_{min} - UDC_{ma}}{4} \quad (55)$$

which resulted in $r_{cg} = 6.35$ mm and is visualized in both subplots as continuous red line. The equation is defined in a way that the mechanical clearance is considered. The distances ODC_{max} , ODC_{min} , UDC_{max} and UDC_{min} , were measured at the locations shown in Fig. 9.

The mechanical clearances $\pm \Delta$ are visualized as dashed red lines. For computing the mean radius $\bar{r}(a(f))$, a cut-off frequency of $f = 10$ Hz was chosen due to the drift-off of the acceleration results $a(f)$ and respectively to the radius.

For both sensors $\bar{r}(a(f))$ lies in between the boundaries of the mechanical clearance, whereby sensor ICM-20948 shows slightly better results.

6. Conclusion

The results of the measurements and data analysis demonstrates that the calibration parameters obtained in a static manner are also valid for dynamic measurements.

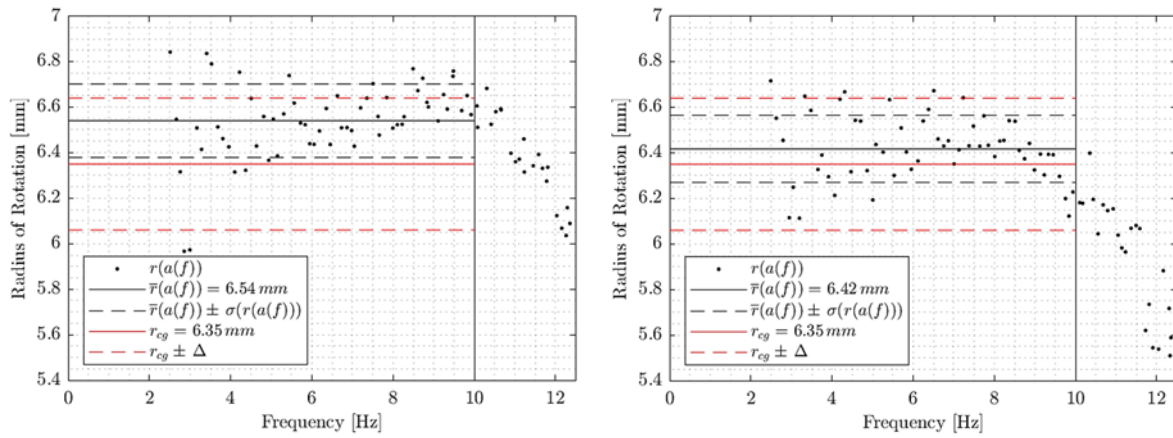


Fig. 8. Computed values of displacement for each of the dynamic measurement are shown in comparison to the radius measured with a calliper gauge for the sensor with the MPU-9250 chip (left) and for ICM-20948 (right). Data from the radius determined from the measured acceleration are displayed as black dots. In the range from 0 Hz to 10 Hz: Average radius represented by a black dashed line; Mean measured radius determined with a calliper gauge shown as red line; Error bounds of the measured radius are visualized as red dashed lines.

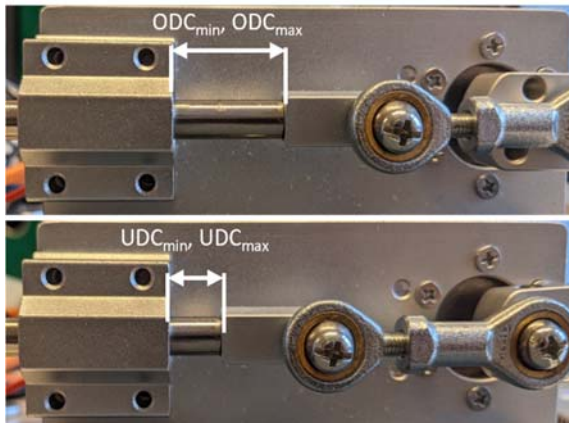


Fig. 9. Measurement position of the maximum and minimum ODC and UDC while forcing the platform in both horizontal directions by hand. The values are used for the clearance determination of the slider-crank mechanism.

The implementation via the method of variable projection avoids the Gibbs error and as well spectral leakage [17] associated with direct FFT methods, resulting in more accurate results. The results, presented in this article verify that a sensor, calibrated with the introduced static calibration method, can be applied for dynamic measurements with significant motion.

7. Future Improvements

The backlash as can be seen from the peaks in Fig. 6 is currently the source of error, improving a new design can avoid this. Further above 12 Hz, the motor cannot achieve to go on higher frequencies. A more powerful drive of higher quality can enable a wider bandwidth of tests.

References

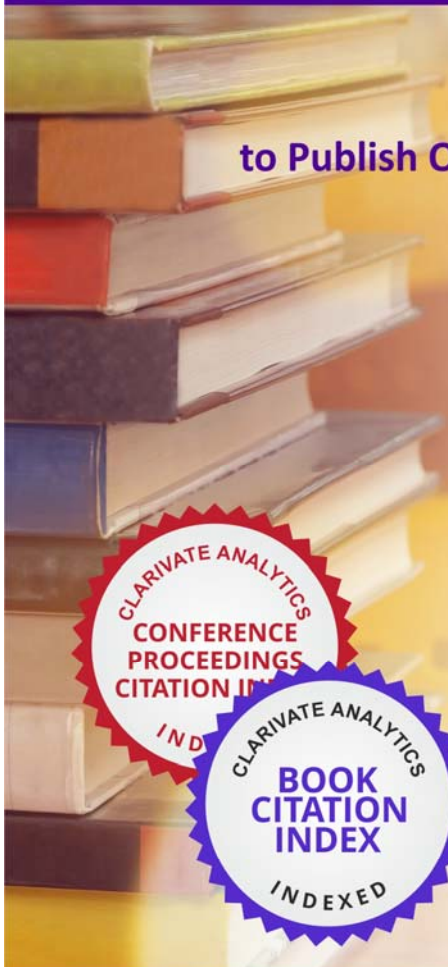
- [1]. E. Lang, et al., Static Calibration and Dynamic Verification of a 3-axis Accelerometer Using the Method of Variable Projection, in *Proceedings of the 7th International Conference on Sensors Engineering and Electronics Instrumentation Advances (SEIA'2021)*, Palma de Mallorca, Spain, 22-24 September 2021, , pp. 33-38.
- [2]. M. Rollett, et al., A Miniature Multi-Sensor System and its Application in a Condition Monitoring, in *Proceedings of the 6th International Conference on Sensors Engineering and Electronics Instrumentation Advances (SEIA'2020)*, 23-25 September 2020, pp. 75-81.
- [3]. B. Künne, Köhler/Rögnitz Maschinenteile 2, 10. Auflage, 2008 (in German).
- [4]. Seong-hoon Peter Won, Farid Golnaraghi, A triaxial accelerometer calibration method using a mathematical model, *IEEE Transactions on Instrumentation and Measurement*, Vol. 59, Issue 8, 2009, pp. 2144-2153.
- [5]. F. Camps, S. Harasse, A. Monin, Numerical calibration for 3-axis accelerometers and magnetometers, in *Proceedings of the IEEE International Conference on Electro/Information Technology (EIT'09)*, 2009, pp. 217-221.
- [6]. G. D'Emilia, A. Gaspari, E. Natale, Dynamic calibration uncertainty of three-axis low frequency accelerometers, *Acta IMEKO*, Vol. 4, 2015, pp. 75-81.
- [7]. D. O'Leary, B. Rust, Variable projection for nonlinear least squares problems, *Computational Optimization and Applications*, Vol. 54, Issue 2, 2013, pp. 579-593.
- [8]. P. O'Leary, D. Ninevski, Estimating Parameters of a Sine Wave by the Method of Variable Projection, in *Proceeding of the International Instrumentation and Measurement Technology Conference (I2MTC'21)*, Glasgow, Scotland, May 2021, pp. 1-6.
- [9]. G. H. Golub, V. Pereyra, The differentiation of pseudo-inverses and nonlinear least squares problems whose variables separate, *SIAM Journal on Numerical Analysis*, Vol. 10, Issue 2, 1973, pp. 413-432.
- [10]. H. Graßmann, Die Ausdehnungslehre, T.C.F. Enslin, Berlin, Vol. 1, 1862 (in German).

- [11]. E. O. Brigham, The fast Fourier transform and its applications, *Prentice-Hall, Inc.*, 1988.
- [12]. A. J. Jerri, The Gibbs phenomenon in Fourier analysis, splines and wavelet approximations, *Springer Science & Business Media*, Vol. 446, 2013, pp. 12-32.
- [13]. L. Guo, Z. Fu, Tikhonov regularized variable projection algorithms for separable nonlinear least squares problems, *Complexity, Hindawi*, November 2019, pp. 1-9.
- [14]. G. Golub, V. Pereyra, Separable nonlinear least squares: the variable projection method and its applications, *Inverse Problems*, Vol. 19, 2003, pp. R1-R26.
- [15]. IEEE, IEEE Standard for Digitizing Waveform Recorders, *IEEE Std*, 1057-2017 (Revision of IEEE Std 1057-2007), pp. 28-40, 2018.
- [16]. S. Wold, K. Esbensen, P. Geladi, Principal component analysis, *Chemometrics and Intelligent Laboratory Systems*, Vol. 2, Issues 1-3, 1987, pp. 37-52.
- [17]. Douglas A. Lyon, The discrete Fourier transform, Part 4: Spectral Leakage, *Journal of Object Technology*, Vol. 8, Issue 7, 2009.



Published by International Frequency Sensor Association (IFSA) Publishing, S. L., 2021
(<http://www.sensorsportal.com>).

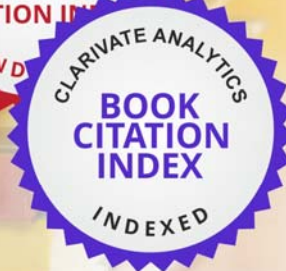




10 Top Reasons

to Publish Open Access Books with IFSA Publishing

- Indexed in Book Citation Index (Web of Science)
- Copyrights belong to Authors (CC-BY)
- The maximum number of pages is not limited
- Very reasonable publication fees
- High visibility
- All book types accepted
- Available in different formats: electronic and print
- Freely available online
- High quality standards
- Authors benefit from IFSA Membership

https://www.sensorsportal.com/HTML/IFSA_Publishing.htm

Digital Magnetometer Based on Giant Magneto Impedance Effect: a Feasibility Study

* **Papa Silly Traore and Mamaye Inès Correa**

Ecole Supérieure Polytechnique (ESP), Université Cheikh Anta Diop (UCAD), Dakar, Sénégal

Tel.: + (221)773999941

E-mail: papasilly.traore@esp.sn

Received: 12 July 2021 / Accepted: 27 September 2021 / Published: 31 October 2021

Abstract: The presented work deals with a feasibility study related on the implementation of digital Giant Magneto-Impedance (GMI) magnetometer (sensor operating in closed-loop). The proposed measurement chain mainly includes an analog-to-digital conversion (ADC) and a digital amplitude demodulation based on a Digital Down Conversion (DDC). In this configuration, the voltage is digitized as close as possible to the sensing element. The DDC include digital mixer and filtering. The transfer function of the overall sensor in open-loop is modelled so as to discuss the stability of the digital magnetometer regarding the processing delay and the sensitivity. Simulations were performed using Matlab-Software with a different set of parameters of the sensor in order to discuss the stability of the magnetometer according to the time delay. The obtained results showed that with a careful adjustment of the sensor sensitivity and the decimation ratio of the digital filter associated with the digital demodulation, the digital magnetometer could be stable in closed-loop.

Keywords: Digital demodulation, Magnetometer, Processing time-delay, Giant Magneto Impedance (GMI) sensor.

1. Introduction

Magnetic sensors are used in a wide variety of applications ranging from high density magnetic recording, non-contact current measurement, to spatial, military and biomedical applications [1]. A non-exhaustive list of these measurement devices may include Fluxgates, inductive sensors, Anisotropic Magnetoresistance (AMR), Giant Magnetoresistance (GMR) sensors, etc. [1]. Over the past two decades, the Giant Magneto-Impedance (GMI) effect has been intensively studied due to its attractive potential for realizing a highly sensitive magnetic sensor [2, 3]. It is defined by a high impedance variation of a ferromagnetic material when it is supplied by a high frequency (HF) excitation current and submitted to an external magnetic field [4]. It has been shown that

GMI sensors offer several advantages compared to conventional sensors. Some of the decisive advantage is the high sensitivity, the potential for miniaturization and the low energy consumption.

A typical configuration of GMI sensor is shown in Fig. 1. It requires a high frequency excitation current provided by an oscillator associated to a voltage-to-current converter. When the sensing element (the ferromagnetic material) is submitted to an external magnetic field, Hz, to be measured, the voltage across the sensing element is amplitude modulated by the measured field. A demodulator is generally used to have the information of the measured field. The relation between the sensor output and the magnetic field is characterized by the sensitivity. The GMI characteristic is strongly nonlinear. To realize a sensor, it is generally magnetically biased in the region

having the maximum of sensitivity. Biasing creates an offset at the sensor output corresponding to the impedance value at the bias point. A difference amplifier is generally used to suppress the offset that could be affected by temperature and strength [5, 6].

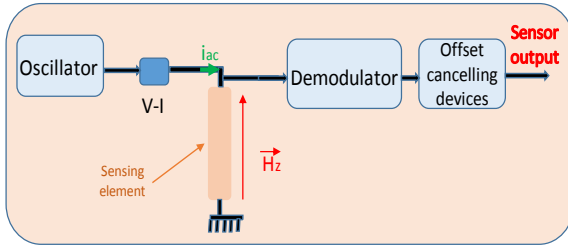


Fig. 1. Hardware architecture of a typical off-diagonal GMI sensor.

In the context of high sensitivity, the equivalent magnetic noise level need to be improved [7, 8]. It characterizes the smallest magnetic field that the sensor can measure. It is defined by the ratio between the voltage noise spectral density (including the electronic conditioning noise and the noise of the sensing element) and the sensitivity of the sensor. Actually, all GMI sensors are associated with an analog electronic conditioning and several studies show that the equivalent magnetic noise is limited in the $1/f$ region by the intrinsic noise of the sensing element attributed to the fluctuation of the magnetization movement. In the white noise region, the smallest magnetic field that the sensor can measure is limited by the electronic conditioning noise [9]. The ultimate noise of the sensing element is not yet achieved in this region. In our recent work [10 - 13], we have introduced the digital concept in order to reduce the electronic conditioning noise so as to achieve the ultimate noise performance. The proposed concept is based on a Digital Down Converter (DDC) for a quadrature digital demodulation. The voltage across the sensing element (generally in off-diagonal configuration for high sensitivity application [9]) is digitized as close as possible to the sensing element. However, as most of sensitive elements, the response to the magnetic field of the GMI element is strongly non-linear. It is not possible to consider them as magnetometers (sensor operating in closed loop) if they are used without suitable conditioning electronics. In order to overcome this problem, a controlled system in which the sensing element works around an operating point in a constant field is necessary. This is done using field feedback, as in the case of many magnetometers (fluxgates, SQUIDS [1], etc.).

The use of the digital concept is generally accompanied by a delay which can destabilize the functioning of the sensor in closed loop system and affects performance of the sensor. The idea behind this article is to evaluate the transfer function of the sensor

and to discuss the stability of the digital GMI magnetometer.

This article is organized as follows. The principle of a GMI magnetometer is presented in Section 2. The hardware architecture of the digital GMI sensor is given in Section 3. Section 4 is devoted to modeling the transfer function of the sensor. Discussion on the sensor stability are given in Section 5. This is followed by a general conclusion.

2. Operating Principle of a GMI Magnetometer

A magnetometer has to exhibit a correct linearity and dynamic range of magnetic field. This can be done, in the GMI magnetometer, using a negative feedback method, by applying a negative magnetic field. The principle of this type of implementation is given in Fig. 2 where the variation of external magnetic field, H_z , around the operating point, is the quantity to be measured. This field-locked loop principle is common to several magnetometers [2].

In this concept, the GMI element ensure the transformation of the magnetic field into voltage through the transfer function, T_d , corresponding to the sensitivity of the open loop sensor. We assume that it is constant in the pass band of the magnetometer. For proper operation of GMI magnetometer, the sensing element is subjected to the difference between the external magnetic field to be measured, H_z , and that created by the feedback, H_{cr} . The feedback magnetic field is generated by a coil wound around the GMI wire. The closed-loop ensures that these two fields are opposed so that its difference is null. By doing so, the GMI wire element is always subjected to the same magnetic field. This structure allows to overcome the problems of non-linearity of the response regarding the measured field.

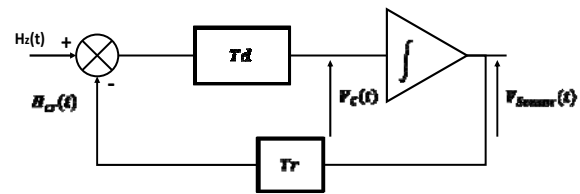


Fig. 2. Principle of the magnetic feedback loop.

The voltage at the output of the magnetometer can be expressed as:

$$V_{sensor} = \frac{T_d}{j\omega} (H_z - T_r * V_{sensor}) = \frac{B_{ext}}{T_r} \left(\frac{1}{1 + \frac{j\omega}{T_d T_r}} \right), \quad (1)$$

where T_r is the transfer function of the feedback loop.

Assuming that $|T_d T_r| \gg j\omega$, the output of the magnetometer is given by:

$$V_{\text{sensor}} \approx \frac{B_{\text{ext}}}{T_r} \quad (2)$$

According to Eq. (2), the output voltage of the sensor depends only on the gain of the feedback chain, T_r . This result is particularly important because it shows that the condition $T_r \gg j\omega/T_d$ allows to overcome the imperfections of the direct chain, T_d , due to the presence of distortion and its gain fluctuations (whether these fluctuations result from an aging of the material, a variation in the experimental conditions). The condition $T_r \gg j\omega/T_d$ is achieving if the field sensitivity, T_d , of the sensing element is very high. The presence of an integrator following the direct chain transfer allow to guarantee this relation, and therefore ensures the absence of static error at the output.

3. The Digital GMI Sensor

The architecture of the digital GMI sensor (representing the direct chain of the magnetometer) is presented in Fig. 3. The proposed concept is based on a new digital electronic conditioning for the high sensitivity GMI magnetic sensor and based on a Field Programmable Gate Array (FPGA).

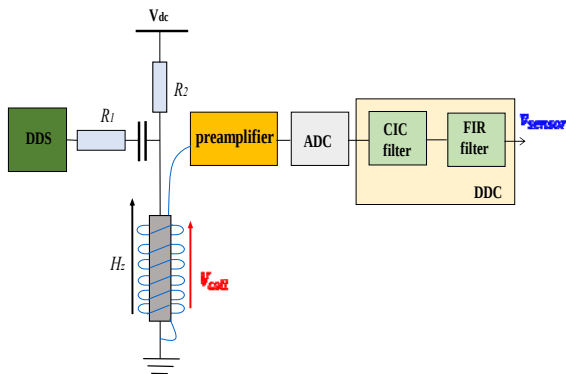


Fig. 3. Hardware architecture of the off-diagonal GMI sensor using a Direct Digital Synthesizer (DDS) and a Digital Down Converter (DDC).

As presented in our recent work [10, 13, 15] a Direct Digital Synthesizer (DDS) supplied the High frequency (HF) excitation current for the GMI sensing element, through a resistor R_1 . This DDS is mainly made of a Numerical Controlled Oscillator (NCO) associated to a Digital-to-Analog Converter (DAC). A dc current (provided by a battery, V_{dc} , and a resistor R_2) is also used so as to remove the bamboo domain [14]. The voltage across the sensing element is optionally amplified by a low-noise preamplifier before being digitized by an analog-to-digital converter (ADC). At the output of the ADC, the data are then transmitted to a Digital Down Converter (DDC) for a quadrature lock-in detection.

The voltage across the sensing element is optionally amplified by a low-noise preamplifier before being digitized by an analog-to-digital converter (ADC). At the output of the ADC, the data are then transmitted to a Digital Down Converter (DDC) for a quadrature lock-in detection. This DDC include a digital multiplier and a cascade of two low-pass digital filter: a Cascade Integrator Comb (CIC) decimation filter and a Finite Impulse Response (FIR) filter. Promising performance of $1.8 \text{ pT}/\sqrt{\text{Hz}}$ (roughly comparable to the best reported in the state of the art) are obtained in the white noise region that shows the potential of the proposed concept in the realization of high sensitivity sensors [12, 13].

4. Sensor Transfer Function

The objective of this section is to model the sensor transfer function in order to discuss the stability of the magnetometer. The concept presented in Fig. 2 can be divided into 2 parts, the excitation system associated with the sensing element (made of the DDS and the sensing element) and the demodulation stage (including the ADC and the DDC). The transfer function of each parts is detailed hereafter.

4.1. The Excitation System and the Sensing Element

The transfer function of the sensitive element is defined by the ratio between the voltage across the sensitive element, V_c , and the measured field, H_{meas} . The transfer function, H_1 is such that:

$$H_1 = \frac{v_c}{H_z} = \frac{Z_{21} \times I_{ac}}{H_z} = S_\Omega \times I_{ac} = S_v, \quad (3)$$

where

- I_{ac} is the amplitude of the excitation current;
- Z_{21} is the impedance of the sensing element in off-diagonal configuration;
- S_Ω and S_v are the intrinsic sensitivity of the sensing element in Ω/T (Ohm per Tesla) and the voltage sensitivity in V/T , respectively.

The voltage across the sensitive element is amplified by a preamplifier, having a gain, G_{preamp} . We assume here that the preamplifier gain remains constant in the bandwidth of the sensor. The voltage, V_{preamp} , at the preamplifier output is given by [16]:

$$V_{\text{preamp}} = G_{\text{preamp}} \times v_{\text{sens}} \times H_z = G_{\text{preamp}} \times S_v \times H_z \quad (4)$$

4.2. The Demodulation Stage

At the output of the preamplifier, the voltage is first digitized before being transmitted to a digital mixer and filtered by a 3rd order CIC decimation (also known as Hogenauer filter) with a decimation factor

N_{CIC} [17]. The transfer function of the filter, H_{CIC} , in the frequency domain is given by:

$$H_{CIC}(f) = N_{CIC}^3 e^{3j\pi f(N_{CIC}-1)} = G_{CIC} e^{j\phi}, \quad (5)$$

where G_{CIC} is the gain of the filter.

The delay due to the 3rd order CIC filter is given by (6) [16]:

$$\tau_{cic} = \frac{\partial \phi}{\partial \omega} = -\frac{\partial \left(\frac{3}{2} \omega (N_{cic}-1) \right)}{\partial \omega} = \frac{3}{2} (N_{cic}-1) \times \frac{1}{F_s} \quad (6)$$

At the CIC filter output, A FIR filter is used to fix the final bandwidth of the baseband. The transfer function of this a FIR filter, H_{FIR} , is given in the frequency domain by:

$$H_{FIR}(f) = \sum_{k=0}^{N_{FIR}} H_k \times e^{-j2\pi f k}, \quad (7)$$

where N_{FIR} is the number of coefficients of the filter. Assuming that $H_{FIR}(f) = V_{out}(f)/X(f)$, where $X(f)$ and $V_{out}(f)$ represent respectively the input and the output of the FIR filter in the frequency domain; the output of the sensor, v_{out} , can be expressed as:

$$v_{out}(f) = \sum_{k=0}^{N_{FIR}} H_k \times x(f) \times e^{-j2\pi f k} = G_{FIR} \times X(f) \times e^{-j2\pi f Z}, \quad (8)$$

where G_{FIR} is the FIR filter gain and Z , the number of delay stages. The delay, τ_{FIR} , due to the FIR filter is a function of the number of delay stages required for the filter implementation. For a filter with symmetrical coefficients (as the case in GMI sensor), the number of delay stages is given by [11, 12]:

$$Z = \frac{N_{FIR}-1}{2} \quad (9)$$

In GMI sensors, the choice of using FIR filter with symmetrical coefficients is justified by the will to reduce the delay of the demodulation stage [12], which can cause the instability of the magnetometer. As a results, the delay, τ_{FIR} , due to the FIR filter is expressed as:

$$\tau_{FIR} = \frac{Z}{F_s} = \frac{N_{FIR}-1}{2} \times \frac{1}{F_s} \quad (10)$$

The transfer function, F_{sensor} , of the sensor defined as the ratio between the output of the FIR filter and the measured magnetic field can be expressed as [17]:

$$F_{sensor}(f) = S_v \times G_{preamp} \times G_{DDC} \times e^{-j2\pi f \left(\frac{N_{FIR}-1}{2} + \frac{3[N_{CIC}-1]}{2} \right)}, \quad (11)$$

where G_{DDC} is the total gain of the DDC given by:

$$G_{DDC} = G_{CIC} * \frac{1}{2} * G_{FIR} \quad (12)$$

The $\frac{1}{2}$ factor is due to the 6 dB losses during mixing.

At the output of the integrator (necessary for proper operation of the magnetometer), the transfer function is given by:

$$F_{out}(f) = \frac{K}{1 + j\frac{f}{f_0}} S_v * G_{preamp} * G_{DDC} * e^{-j2\pi f \left(\frac{N_{FIR}-1}{2} + \frac{3[N_{CIC}-1]}{2} \right)}, \quad (13)$$

where K and f_0 are the gain and the cutoff frequency of the integrator.

5. Stability in Closed-loop

The stability of closed-loop systems can be studied starting from the open-loop system by quantifying the stability margins: gain and phase margins. It is therefore possible, knowing the transfer function of the sensor (open-loop), to discuss the stability of the magnetometer (closed-loop). In general, the magnetometer is stable if it has a positive gain margin and a positive phase margin.

Simulations were then realized using Matlab software in order to discuss the stability of the sensor in closed-loop according to the transfer function given in Eq. (13). The first simulations were conducted with the same parameters set in our recent work [10] to realize a sensor in open loop. The set of parameters was: $N_{CIC}=250$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$. Fig. 4 shows the Bode diagram of the open-loop sensor for a sensitivity, S_v of 620 kV/T.

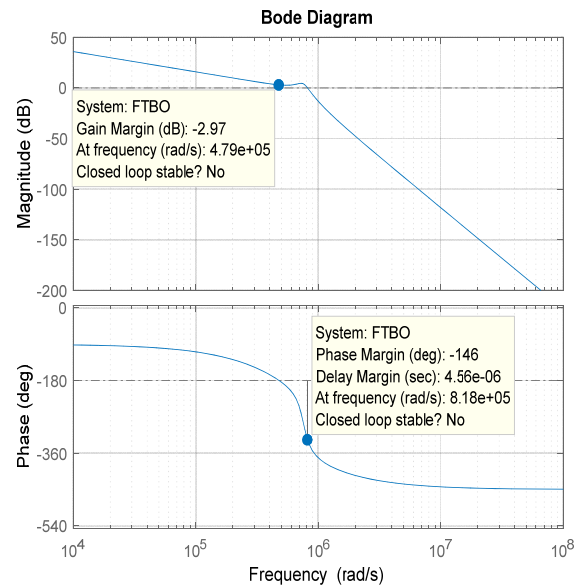


Fig. 4. Bode diagram of the open-loop sensor. The setting parameters was: $S_v=620\text{kV/T}$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$; $N_{CIC}=250$.

A gain margin of -2.97 dB and a phase margin of -146° is obtained that leads us to an unstable functioning of the magnetometer. Using this parameters, the estimated delay is of $3.32 \mu\text{s}$.

A second simulation was conducted for the same delay to see the influence of the sensitivity on the magnetometer stability. According to (3), the sensitivity can be reduced by reducing the amplitude of the I_{ac} high frequency excitation current. The setting parameters was: $N_{CIC}=250$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$. Fig. 5 shows the Bode diagram of the open-loop sensor for a sensitivity, S_v of 100 kV/T .

A gain margin of 12.9 dB and a phase margin of 71° is obtained that leads us to a proper functioning of the magnetometer with this setting parameters. Using this parameters, the estimated delay is also of $3.32 \mu\text{s}$.

The results of the simulation show that for a given delay, there are a maximum of sensitivity to ensure the functioning of the closed loop sensor.

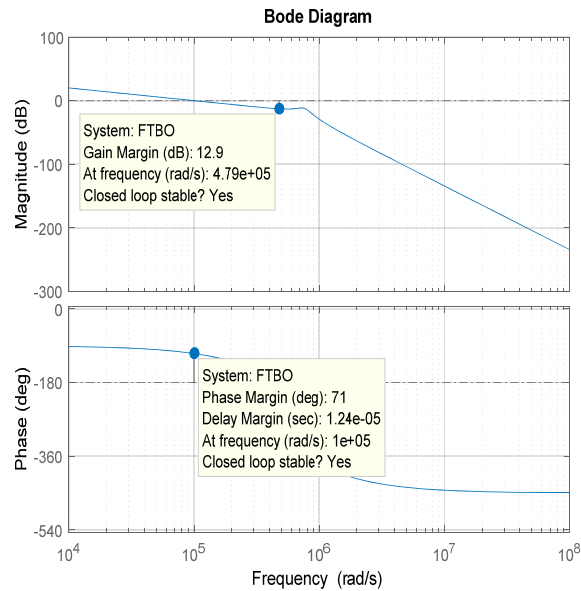


Fig. 5. Bode diagram of the open-loop sensor. The setting parameters was: $S_v=200 \text{ kV/T}$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$; $N_{CIC}=250$.

Simulations were then carried out to show the impact of the time-delay on the stability of the magnetometer for a given sensitivity. The sensitivity value of 620 kV/T , measured in our previous work [13] where the sensor operates in open loop, is retained in our simulation. The variation of the delay is done by adjusting the decimation ratio of the CIC filter or the number of filter coefficients. Fig. 6 shows the Bode diagram of the open-loop sensor for the given parameters hereafter: $N_{CIC}=100$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$.

A gain margin of 3.8 dB and a phase margin of 35.9° is obtained that leads us to a proper functioning of the magnetometer with this setting parameters. Using this parameters, the estimated delay is of $1.52 \mu\text{s}$.

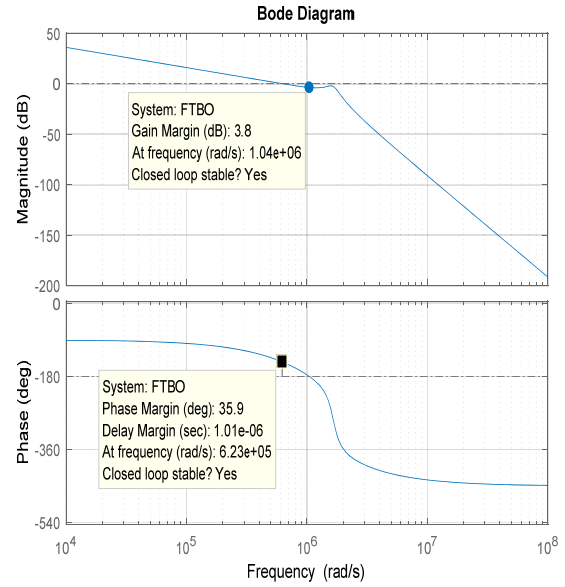


Fig. 6. Bode diagram of the open-loop sensor. The setting parameters was: $S_v=620 \text{ kV/T}$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$; $N_{CIC}=100$.

Another simulation was conducted by reducing the decimation ratio of the CIC filter (consequently reducing the delay according to Eq. (6)) in order to analyze the impact of the time-delay. Fig. 7 shows the Bode-diagram of the open-loop sensor. The setting parameters was $S_v=620 \text{ kV/T}$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$; $N_{CIC}=160$.

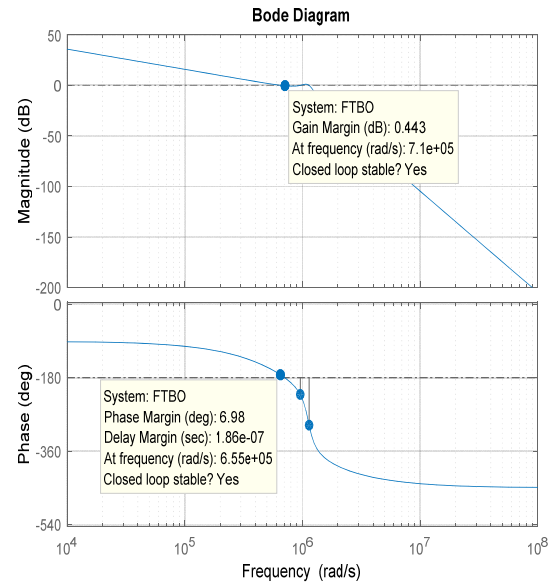


Fig. 7. Bode diagram of the open-loop sensor. The setting parameters was: $S_v=620 \text{ kV/T}$; $G_{preamp}=1$; $G_{DDC}=40$; $N_{FIR}=83$; $N_{CIC}=160$.

An estimated delay of $2.24 \mu\text{s}$ is obtained. A gain margin and a phase margin of 0.44 dB and 6.98° is obtained, respectively that leads us to a stable magnetometer. It should be noted that if the system is

at the limit of stability or if the stability margins are not sufficient (as in the case in Fig. 7), parasites could potentially introduce instabilities of the closed-loop system.

Fig. 8 shows the Bode-diagram for this parameters: $S_v=620\text{kV/T}$; $G_{\text{preamp}}=1$; $G_{\text{DDC}}=40$; $N_{\text{FIR}}=83$; $N_{\text{CIC}}=200$. With this setting parameters, the decimation ratio is increased resulting on the increase of the processing time-delay.

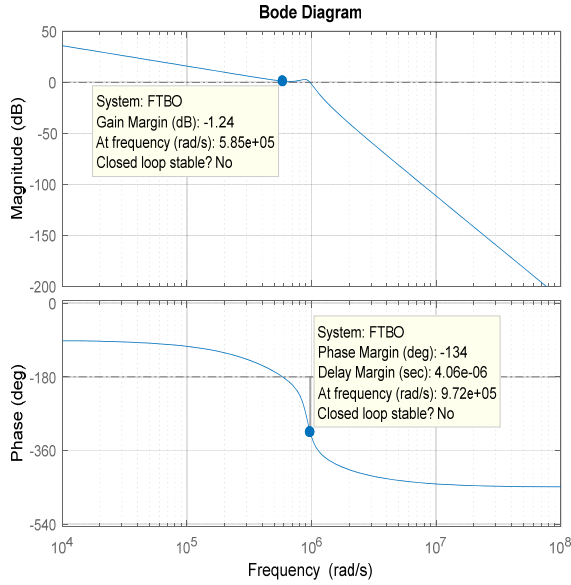


Fig. 8. Bode diagram of the open-loop sensor. The setting parameters was: $S_v=620\text{kV/T}$; $G_{\text{preamp}}=1$; $G_{\text{DDC}}=40$; $N_{\text{FIR}}=83$; $N_{\text{CIC}}=200$.

An estimated delay of $2.72 \mu\text{s}$ is obtained. A gain margin and a phase margin of -1.24 dB and -134° is obtained, respectively that leads us to a unstable magnetometer. Regarding Fig. 6, Fig. 7 and Fig. 8, results show that for a given sensitivity, there are a maximum of time-delay to ensure the functioning of the closed loop sensor.

In summary, the sensor parameters (sensitivity, delay) must be chosen judiciously in order to ensure the stability of the closed-loop magnetometer. These results were confirmed by practice.

In fact, firsts measurements were then realized in order to prove the proposed modelling and simulation. The block diagram of the proposed digital GMI magnetometer is given in Fig. 9. The polarization stage of the measurement chain is made of a Direct Digital Synthesizer (DDS), a battery and the two injection resistors, R_g et R_{bias} . The DDS provide the sinusoidal signal to the GMI element, through the resistor R_g . In a ferromagnetic wire having a circumferential anisotropy (as the case in the use GMI element), a dc current is necessary in order to observe the off-diagonal component. The dc current creates a circumferential dc field in the ferromagnetic wire. This dc field combines with the axial field to be measured produces a helical field which magnetizes the conductor along a helical path. This dc current is

obtained using a battery and the resistor R_{bias} . The voltage across the pick-up coil which is amplitude-modulated by the measured field, is first amplified by a low noise preamplifier, having a gain, G_{preamp} , before being digitized by an analog-to-digital converter (ADC) at a sampling frequency (F_s).

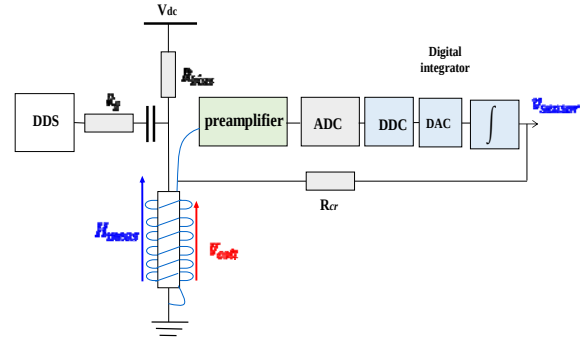


Fig. 9. Hardware architecture of a digital GMI magnetometer.

At the output off the DDC, data are transmitted to the DAC and then to a digital-to-analog converter (DAC). The DAC output is applied at the input of an integrator necessary to overcome the imperfections of the direct chain [18, 19]. The voltage at the output of the sensor is used to create the feedback magnetic field, H_{cr} . This is applied to the GMI wire via the resistor, R_{cr} and a coil wound around the GMI wire.

Closed-loop measurement has then been operated for the digital magnetometer in order to compare the results of the theoretical model with the measurement. The comparison procedure consisted in fixing a given delay (by fixing the decimation ratio of the CIC filter) and by varying the current I_{ac} so as to obtain the limit value of the current I_{ac} ensuring the stability of the magnetometer.

Fig. 10 shows the comparison of the maximum value (threshold) of the I_{ac} excitation current obtained by measuring and by our theoretical model (according to Eq. (11)) for different value of the decimation filter.

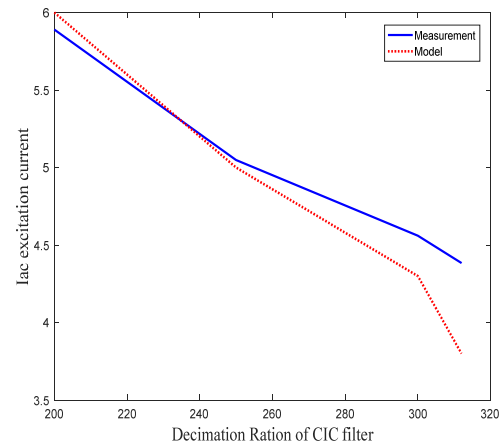


Fig. 10. Maximum value of excitation current in function of the decimation filter.

The obtained results validate our proposed theoretical model. Ongoing will focus on the characterization of the digital magnetometer.

6. Conclusions

In this paper, we have investigated the impact of the delay in the stability of the digital GMI magnetometer. The presented electronic conditioning is mainly based on digital down converter including low pass decimation filter induces time-delay due to processing. Each function of the open loop sensor is modelled in order to discuss the stability of the closed-loop by analyzing the stability margins: gain and phase margins. Obtained results show the possible operating of the digital magnetometer by making a trade-off between the sensitivity (by the I_{ac} excitation current) and the delay (by the decimation ration). Comparison between the proposed theoretical model and measurement of the digital magnetometer were performed. Results validates the theoretical approach for digital GMI magnetometer applications.

References

- [1]. P. Ripka, Magnetic Sensors and Magnetometers, *Artech House Publisher*, 2001.
- [2]. K. V. Rao, F. B. Humphrey, J. L. Costa-Kramer, Very large magnetoimpedance in amorphous soft ferromagnetic wires, *Journal of Applied Physics*, Vol. 76, Issue 10, 1994, pp. 6204-6208.
- [3]. L. Panina, K. Mohri, Magneto-impedance effect in amorphous wires, *Applied Physics Letters*, Vol. 65, 1994, pp. 1189-1191.
- [4]. E. P. Harrison, G. L. Turney, H. Rowe, Electrical properties of wires of high permeability, *Nature*, Vol. 135, Issue 3423, 1935, pp. 961.
- [5]. J. Nabias, A. Asfour, J. P. Yonnet, Temperature Dependence of Giant Magnetoimpedance in Amorphous Microwires for Sensor Application, *IEEE Transactions on Magnetics*, Vol. 53, Issue 4, November 2016.
- [6]. J. Nabias, A. Asfour, J. P. Yonnet, The Impact of Bending Stress on the Performance of Giant Magneto-Impedance (GMI) Magnetic Sensors, *Sensors*, Vol. 17, Issue 3, March 2017.
- [7]. B. S. Sandacci, D. Makhnovskiy, L. Panina, K. Mohri, Y. Honkura, Off-Diagonal Impedance in Amorphous Wires and its Application to Linear Magnetic Sensors, *IEEE Transactions on Magnetics*, Vol. 40, 2004, pp. 3505-3511.
- [8]. D. Ménard, D. Seddaoui, L. G. C. Melo, A. Yelon, B. Dufay, S. Saez, C. Dolabdjian, Perspectives in Giant Magnetoimpedance Magnetometry, *Sensors Letters*, Vol. 7, Issue 3, 2009, pp. 429-432.
- [9]. B. Dufay, S. Saez, C. P. Dolabdjian, A. Yelon, D. Ménard, Characterization of an optimized Off-Diagonal GMI-based Magnetometer, *IEEE Sensor Journal*, Vol. 13, Issue 1, January 2013, pp. 379-388.
- [10]. P. S. Traoré, A. Asfour, J. P. Yonnet, C. Dolabdjian, Noise Performance of SDR-Based Off-Diagonal GMI Sensors, *IEEE Sensors Journal*, Vol. 17, Issue 19, October 2017, pp. 6175-6184.
- [11]. P. S. Traoré, A. Asfour, J. P. Yonnet, Off-Diagonal GMI Sensors with Software Defined Radio Detector: Implementation and performance, *IEEE Transactions on Magnetics*, Vol. 53, Issue 4, 2017.
- [12]. P. S. Traoré, A. Asfour, J.-P. Yonnet, C. Boudinet, Introduction of real-time digital processing techniques for the high-sensitivity GMI sensors, *International Journal of Applied Electromagnetics and Mechanics*, Vol. 59, Issue 2, 2019, pp. 455-463.
- [13]. P. S. Traoré, A. Asfour, J. P. Yonnet, Design Approach for an Off-Diagonal Giant Magneto Impedance Sensor Based on Field Programmable Gate Array, *Sensors and Transducers*, Vol. 245, Issue 6, October 2020, pp. 20-26.
- [14]. L. Ding, S. Sebastien, C. Doladjan, P. Ciureanu, L. G. C. Melo, A. Yelon, D. Menard, Intrinsic giant magnetoimpedance noise reduction by DC bias, *Sensors Letters*, Vol. 5, Issue 4, 2007, pp. 176-179.
- [15]. P. S. Traore, A. Asfour, P. A. Fam, J.-P. Yonnet, High Sensitivity digital GMI sensor based FPGA, in *Proceedings of the 6th International Conference on Sensors and Electronic Instrumentation Advances (SEIA'2020)*, Porto, Portugal, 23-25 September 2020, pp. 65-69.
- [16]. P. S. Traore, M. I. Correa, C. A. B. Mbodji, High Sensitivity digital GMI sensor based FPGA, in *Proceedings of the 7th International Conference on Sensors and Electronic Instrumentation Advances (SEIA'2021)*, Palma de Mallorca, Spain, 22-24 September 2021, pp. 132-135.
- [17]. Hogenauer E. B., An economical class of digital filters for decimation and interpolations, *IEEE Transaction on Acoustics, Speech and Signal Processing*, Vol. 29, Issue 2, 1981, pp. 155-162.
- [18]. B. Dufay, S. Saez, C. P. Dolabdjian, A. Yelon, D. Ménard, Characterization of an optimized Off-Diagonal GMI-based Magnetometer, *IEEE Sensor Journal*, Vol. 13, Issue 1, January 2013, pp. 379-388.
- [19]. D. Ménard, D. Seddaoui, L. G. C. Melo, A. Yelon, B. Dufay, S. Saez, C. Dolabdjian, Perspectives in Giant Magnetoimpedance Magnetometry, *Sensors Letters*, Vol. 7, Issue 3, 2009, pp. 339-342.
- [20]. P. S. Traoré, S. Konan, A. Asfour, J.P. Yonnet, Analysis of the impact of the processing time-delay on the stability of a digital GMI magnetometer, in *Proceedings of the IEEE Sensors*, 31 October-4 November 2021.



Modified Ultrasonic Liquid Level Transducer Using Wave Intensity as the Informative Parameter

^{1,*}Haraprasad MANDAL, ²Madhuchhanda MITRA
and ²Satish Chandra BERA

¹ Department of Applied Electronics and Instrumentation Engineering, Saroj Mohan Institute of Technology, Guptipara, Hooghly-712512, India

² Instrumentation Engineering Section, Department of Applied Physics, University of Calcutta, 92, A.P.C. Road, Kolkata 700009, India

¹ Tel.: +91 9830879652, +917003744207

* E-mail: hprasad.mandal@gmail.com

Received: 14 June 2021 /Accepted: 24 September 2021 /Published: 31 October 2021

Abstract: The conventional ultrasonic liquid level measurement techniques are generally based on time of flight (TOF) measurement technique of reflected sound wave from liquid surface in a storage tank. In the present paper, a modified ultrasonic liquid level transducer is developed using the intensity of a 40 kHz ultrasonic pulsating echo signal reflected from the liquid surface as the sensing parameter. A simple transducer circuit converts this pulsating signal into a D.C. voltage signal which is taken as a measure of the intensity of the reflected pulses obtained from the ultrasonic receiver probe. The characteristic equation showing the relation between the transducer output voltage and liquid level is derived in the paper. A proto type unit is developed and tested experimentally to determine the static characteristic of the proposed ultrasonic level transducer. The experimental results are reported in the paper. A nonlinear static characteristic with very good repeatability is observed.

Keywords: Ultrasonic liquid level transducer, Ultrasonic transmitter-receiver probes, Ultrasonic oscillator, Op- amp, Signal conditioner.

1. Introduction

Accurate and reliable measurement of liquid level in a storage tank is very important in any process plant. Among the different techniques [1-3] of liquid level measurement, the direct technique like dip stick, gauge glass, float, displacer etc. and indirect technique like capacitive, inductive, ultrasonic, nucleonic etc. are widely used. The ultrasonic technique has the great advantage that it is a non-contact technique with better longevity, accuracy and linearity. The conventional ultrasonic technique is based on accurate measurement of time of flight (TOF) between the instants of transmitting and receiving of reflected ultrasonic wave

from the liquid surface in a storage tank. But the measuring unit is a complicated microprocessor or microcontroller or computer based system where very accurate measurement of time interval is possible. This time interval is linearly related with the liquid level and the measurement technique is very accurate. Various simplified ultrasonic techniques are still being reported by many research groups.

A. Rocchi, *et al.* [4] have studied in detail, the time of flight technique of measurement of liquid level by using simple ultrasonic sensor. In this study they have analyzed the effects of atmospheric temperature and humidity on the level measurement and have determined the optimum condition of the measuring

system for better accuracy. For accurate measurement of the geometrical and acoustic characteristic parameters of wood and plastic samples from measurement of time of flight,

P. Lasaygues, *et al.* [5] have experimentally applied two coded excitation methods like chirp-coded and wavelet-coded excitation methods. By using two 500 kHz transducers for polyurethane and wood samples, they have shown that the measurement error is 0.13 % minimum in wavelet-coded excitation and 2.3 % maximum in chirp-coded excitation.

A microcontroller based water detection and control system using simple ultrasonic transceiver set has been designed by M. I. Bello, *et al.* [6]. In this technique the water levels of the domestic underground and overhead reservoir tanks have been measured by using time of flight technique.

A non-contact measurement system of liquid petroleum gas (LPG) level in a pressurized LPG tank has been designed and studied by Z. Zakaria, *et al.* [7] using simple ultrasonic sensor mounted above the top surface of the cylinder. In this technique, the ultrasonic wave passes through the cylinder wall and the reflected back from the LPG surface inside the cylinder and the data acquisition system level.

B. Praher, *et al.* [8] have designed an ultrasonic measurement algorithm for the measurement of the thickness of liquid layer between two solid materials using time domain analysis. In this algorithm, the time domain signals received from liquid layer due to multiple reflections are reconstructed to simulate the superimposed signal which is compared with the measured signal to estimate the time of flight of the ultrasonic pulse in a liquid layer and to measure the thickness of the layer.

P. Petlac, *et al.* [9] have applied the commercial of the shelf (COTS) ultrasonic sensors to measure on board aircraft fuel level and quantity. In this measuring system special electronic circuit is designed to develop the high frequency transceiver used in the measurement system.

An accurate time of flight (TOF) measurement technique of ultrasonic echo signal from a liquid surface has been developed by P. Li, *et al.* [10]. In this technique, the exiting ellipse algorithm of TOF measurement is utilized to extract the echo pulse from the ultrasonic echo signal and from the echo pulses a 2D electrical pulse pattern is obtained. The TOF is determined by averaging the two time points of maximum gradients from the elliptical echo pattern.

An accurate dynamic liquid level detection technique is proposed by P. Li, *et al.* [11] using MIMO ultrasonic Transducer array. In this technique the rise and fall of the dynamic liquid level under dynamic condition is detected by applying the virtual element technology on the MIMO ultrasonic level sensor.

M. Suleiman, *et al.* [12] have studied an ultrasonic fluid level measuring system by using the TOF measurement technique. They have studied the proposed measurement system in the range 0.02 m to 4 m with the accuracy of 1 cm.

T. J. Licznarski, *et al.* [13] have proposed an ultrasonic transducer system for accurate measurement of the distance of an object in air. The distance is determined from the measurement of the time interval between the instant of transmitting the signal and the instant of receiving its echo from the object.

Terzic, *et al.* [14] have developed a level measurement system under dynamic condition by using a single ultrasonic sensor and a support vector machine (SVM). In this technique, the measurement error in the raw sensor signal under sloshing effect and temperature variation is minimized by differentiating and smoothing the signal in SVM system.

W. K. Spatt, *et al.* [15] have developed a torsional waveguide in order to measure the liquid depths of different liquid in a mixture. In this technique the time of flight between the incident and reflected wave is found to be a function of liquid level with better sensitivity than the conventional echo technique.

D. W. Lee, *et al.* [16] have proposed a modified ultrasonic method for the measurement of a two phase mixture level. This method is more accurate than the conventional ultrasonic technique to measure liquid level in a two-phase mixture under the high temperature and pressure conditions as well as under the diffused reflection condition from a fluctuated surface of water level. A modified calculation method is developed to determine the correct sound velocity under these conditions and a waveguide is developed to reduce the loss of echo due diffuse reflection and attenuation.

An ultrasonic technique of level measurement has been designed by M. Maribout, *et al.* [17] to measure the level of water and oil in an oil tanker. In this technique, the different acoustic impedances of oil and water in the oil tank produce different signals to the receiver which are correlated with the depths of the liquid in different layers.

A non-invasive technique of level measurement of a liquid in a closed tank under high pressure has been studied by V. E. Sakharov, *et al.* [18] using ultrasonic lamb wave at an optimum frequency of 100 kHz. Here the characteristics of the fundamental and higher order waves passing through the wall of the tank are found to depend on the wall material, wall thickness and the depth of the liquid inside the tank.

E. Vargas, *et al.* [19] have developed an ultrasonic technique for the measurement of liquid level in a closed bottle. In this technique a time of flight measurement method is used from the envelope of echo signal.

An ultrasonic pulse-echo type liquid level measuring technique has been described by A. B. Gillespie, *et al.* [20]. In this technique, the ultrasonic pulse wave travels through a metallic bar or strip towards the liquid surface and the liquid level is estimated from time of flight of reflected echo from a special reflecting structure at the liquid surface.

L. Jakevicius, *et al.* [21] have analyzed the attenuation coefficient of ultrasonic signal in air under isothermal and adiabatic conditions. From this analysis it is shown that the attenuation coefficient of ultrasonic

signal in air is a non-linear function of temperature, relative humidity, pressure and signal frequency.

A microcontroller based ultrasonic distance measurement technique has been studied by S. Y. Yurish [22]. In this time of flight (TOF) technique, the measuring system has been designed by using microcontroller operated ultrasonic smart sensors and universal sensors & transducers interface IC in which the measurement error due to the effect of temperature on sound velocity is eliminated.

In the present paper, an intensity measurement technique of reflected ultrasonic wave from liquid surface in a closed vessel has been studied. The intensity of the echo of ultrasonic wave from the liquid surface is detected and measured by the ultrasonic receiver sensor and the transducer circuit with its output varying non-linearly with the liquid level. The characteristic equation showing the relation between the transducer output and liquid level as well as the liquid surface-receiver probe distance has been derived in the paper. A proto type unit of the proposed level transducer is developed and tested experimentally. The experimental results are reported in the paper. The characteristic graphs obtained from experiment are found to follow the derived equation with better repeatability.

2. Method of Approach

Let an ultrasonic point source of constant power output 'P' is placed at a point 'X' in a free space. Sound waves from this point source moves radially in all directions through the surrounding medium as shown in Fig. 1. If we assume a spherical concentric surface of radius 'R' surrounding the point source then the sound power passing normally through the whole spherical surface of area $A = 4\pi R^2$ is 'P'.

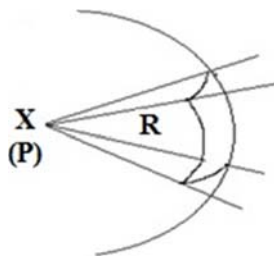


Fig. 1. Propagation of ultrasonic wave from a point source through spherical concentric surface.

So the intensity of sound wave at distance R from an ultrasonic point source is given by

$$I = \frac{P}{A} = \frac{P}{4\pi R^2} \quad (1)$$

Thus the propagation of ultrasonic wave through a medium may be assumed to follow the inverse square

law. Now let us assume that an ultrasonic transmitter-receiver probe set (T_X - R_X) is placed on the cover lid of storage tank as shown in Fig. 2. In the storage tank, the ultrasonic sound wave from the transmitter probe (T_X) moves downwards towards the liquid surface in the storage tank and after reflection from the surface, the reflected echo reaches the receiver probe (R_X). The transmitter probe (T_X) is supplied from a stabilized oscillator circuit to produce an ultrasonic sound wave of constant amplitude and frequency by the transmitter probe. Now in the storage tank, the reflected ultrasonic echo reaching the receiver probe, travels through a distance $d = 2(H - h)$, where 'H' is total height of the storage tank and 'h' is the height of the liquid level inside the tank as shown in Fig. 2. Since the intensity of the ultrasonic sound wave follows inverse square law, so the intensity (I_r) of echo in receiver (R_X) of storage tank may be given by,

$$I_r \propto \frac{1}{d^2} \quad \text{or, } I_r = \frac{K_1}{d^2} = \frac{K_1}{4(H - h)^2}, \quad (2)$$

where K_1 is the constant of proportionality.

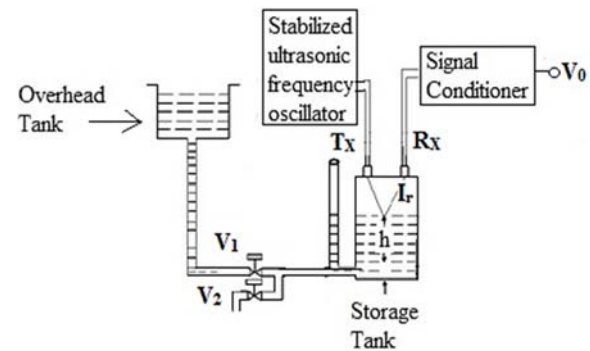


Fig. 2. Schematic diagram of the experimental set-up for the proposed ultrasonic level transducer.

Since the output of the receiver probe is directly proportional to the intensity of the received sound, so the a.c. output (V_1) of the receiver probe may be given by,

$$V_1 \propto I_r \quad \text{or, } V_1 = K_2 I_r = \frac{K_1 K_2}{4(H - h)^2}, \quad (3)$$

where K_2 is the constant of proportionality.

The transducer circuit in the form a signal conditioner circuit as shown in Fig. 2 converts the above a.c. signal output of receiver probe into an amplified dc signal output.

2.1. Measuring Circuit

The measuring circuit designed in the proposed liquid level measuring system consists of a stabilized ultrasonic oscillator circuit supplying the excitation

signal as shown in Fig. 3 and an ultrasonic transmitter probe with its output connected with a signal conditioner or transducer circuit as shown in Fig. 4.

In Fig. 3, the ultrasonic transmitter probe (T_x) is supplied from a stabilized IC555 timer-based oscillator with 50 % duty cycle. The oscillator is designed from an astable multivibrator using the timer IC555 supplied from a stabilized DC source. From the data manual of IC 555 timer circuit, the frequency of oscillation is given by

$$f = \frac{1.44}{(R_A + 2R_B)C} \quad (4)$$

and its duty cycle is given by

$$D = \frac{R_B}{(R_A + 2R_B)} \times 100\% \quad (5)$$

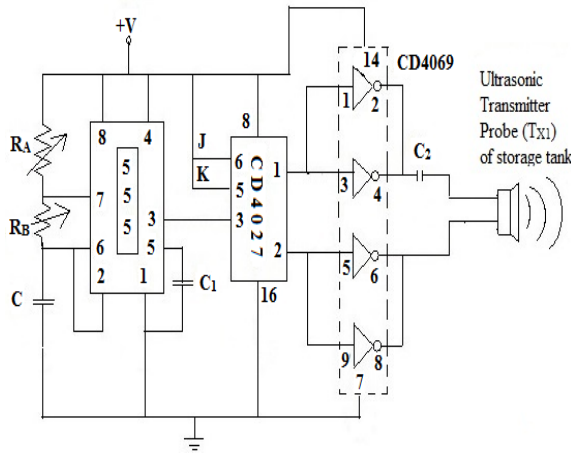


Fig. 3. Ultrasonic transmitter probe supplied from a stabilized oscillator circuit.

In the proposed ultrasonic transmitter circuit as shown in Fig. 3, the frequency of the IC555 timer oscillator is selected at 80 kHz. From this 80 kHz output signal of the timer circuit, two 40 kHz signals with opposite phases are developed by using short circuited JK flip flop IC CD4027. These two signals are used to excite the transmitter probe (T_x) through a buffer stage IC (4069) to produce 40 kHz ultrasonic signal. Since the transmitter probe is mounted on the cover lid of the tank with its transmitting surface facing towards the bottom of the tank, so the ultrasonic wave produced by the transmitter probe in the storage tank propagates towards the liquid surface of the storage tank and after reflection from the liquid surface, the reflected sound wave or echo sound reaches the ultrasonic receiver probe mounted on the same cover lid as shown in Fig. 2. In Fig. 4, the signal conditioner circuit acting as the transducer unit converts the input echo signal received by the receiver probe (R_x) into the dc output voltage signal V_0 . The signal conditioner circuit consists of the non-inverting amplifier circuit with op-amp A_1 , a precision half wave rectifier with

op-amp A_2 and zero adjustment circuit with op-amp A_3 . The a.c output signal of the non-inverting amplifier circuit is given by,

$$V_2 = \left(1 + \frac{R_2}{R_1}\right) V_1 = \left(1 + \frac{R_2}{R_1}\right) \frac{K_1 K_2}{4(H-h)^2} \quad (6)$$

The rectified d.c. output of the precision rectifier circuit with op-amp A_2 is directly proportional to the a.c input signal V_2 . So the d.c. output V_3 is given by,

$$\begin{aligned} V_3 &\propto V_2 \\ \text{or, } V_3 &= K_3 V_2 = \left(1 + \frac{R_2}{R_1}\right) \frac{K_1 K_2 K_3}{4(H-h)^2} \quad (7) \\ \text{or, } V_3 &= \frac{K_4}{(H-h)^2} \end{aligned}$$

where K_3 is the constant of proportionality

$$\text{and } K_4 = \frac{K_1 K_2 K_3}{4} \left(1 + \frac{R_2}{R_1}\right) \quad (8)$$

The output (V_0) of the unity gain differential amplifier circuit using op-amp A_3 is given by

$$V_0 = V_3 - V_Z = \frac{K_4}{(H-h)^2} - V_Z \quad (9)$$

$$\text{or, } V_0 = \frac{K_4}{d^2} - V_Z \quad (10)$$

where $d = H - h$ is the distance between the reflecting surface of the liquid and the ultrasonic transceiver probes placed on storage tank cover lid and V_Z is the zero adjustment voltage input of the unity gain differential amplifier using op-amp A_3 . For $V_Z = 0$,

$$V_0 = \frac{K_4}{d^2} \quad (11)$$

Hence the transducer output V_0 decreases with the increase of the distance between the reflecting surface of the liquid and the transceiver probes, i.e., the transducer output decreases non-linearly with the increase of liquid level. In equation (9) and (10), the sensitivity constant K_4 can be adjusted by varying the gain potentiometer R_2 as shown in equation (8). The zero adjustment voltage V_Z is selected in order to obtain a desired minimum value of the transducer output at zero value of liquid level or at maximum value of liquid surface-receiver probe distance. With the increase of level, the liquid surface-receiver probe distance (d) decreases and the transducer output (V_0) increases as the equation (10). Thus the maximum and minimum values of the transducer output at maximum and minimum values of liquid level respectively are adjusted by varying the gain potentiometer R_2 and the zero adjustment potentiometer R_Z as shown in Fig. 4.

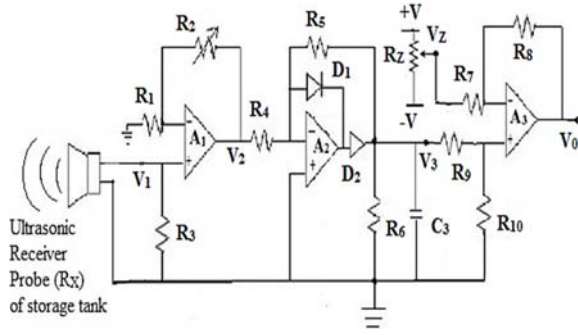


Fig. 4. Ultrasonic receiver probe and transducer circuit.

2.2. Error Calculation in Pulse to DC Signal Conversion Process (by Half Wave Precision Rectifier Circuit with Op-amp A₂)

The amplified pulse signal (V_2) is converted into smooth DC signal with the help of the precision half wave rectifier circuit consisting of op-amp A_2 as shown in Fig. 4 and the capacitive filter C_3 with load resistance R_6 . An error signal is produced in this conversion process which may consist of two parts: error due to noise and error due to ripples.

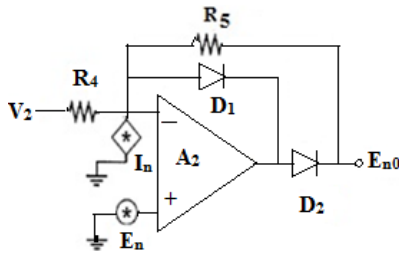


Fig. 4 (a). Noise equivalent of half wave precision rectifier.

From the noise equivalent circuit of the half wave precision rectifier as shown in Fig. 4 (a), the output noise voltage E_{n0} per unit frequency bandwidth can be calculated from the following equation (12).

$$E_{n0}^2 = \left(1 + \frac{R_5}{R_4}\right)^2 E_n^2 + I_n^2 R_5^2 + 4\pi k_B T \left(\frac{R_4 R_5}{R_4} + R_5\right), \quad (12)$$

where k_B is the Boltzmann constant (1.38×10^{-23} J/K) and T is the absolute temperature.

From the manufacturer's datasheet of the selected op-amp (OP07),

$$E_n = 9.6 \times 10^{-9} \text{ V} / \sqrt{\text{Hz}} \text{ and } I_n = 14 \times 10^{-12} \text{ A} / \sqrt{\text{Hz}}$$

Putting these values in (12), we have the output noise voltage for $R_4 = R_5 = 1 \text{ k}\Omega$ and $T = 300 \text{ K}$ given by

$$E_{n0} = 2.59 \times 10^{-8} \text{ V} / \sqrt{\text{Hz}} \quad (13)$$

Hence the error due to noise may assume to be negligible.

The error due to ripples may be estimated from the calculation of the ripple factor of the capacitive filter C_3 with R_6 acting as load shown in Fig. 4. As per the proposed design, the pulse frequency $f = 40 \text{ kHz}$ = ripple frequency, $R_6 = 1 \text{ k}\Omega$ and $C_3 = 220 \text{ }\mu\text{F}$. Hence the ripple factor (r_f) is given by

$$r_f = \frac{1}{2\sqrt{3} f R_6 C_3} = 3.28 \times 10^{-5}$$

Thus the ripple factor in the proposed design is negligible and the additional error introduced in the pulsating signal to DC signal conversion process due to the ripples may also be assumed negligible.

3. Design

The proposed ultrasonic level transducer system is designed by selecting the ultrasonic transmitter and receiver probe units as 40TR-12W, which is commercially available in the market as discrete transmitter and receiver probes. The storage tank which is selected in proposed design is a cylindrical plastic tank of internal height 38 cm and outer diameter 20 cm with a lid cover on which ultrasonic transmitter and receiver probes are mounted by using an adhesive compound like fevi-quick with their sensing surfaces facing towards the liquid surface inside the storage tank. The storage tank is attached with a gauge glass marked with mm scale from which the liquid level inside the storage tank can be measured. Now the excitation circuit of the transmitter sensor is designed for 80 kHz using IC 555 timer based a stable multivibrator circuit as shown in Fig. 3. For 50 % duty cycle, $50 = \frac{R_B}{(R_A + 2R_B)} \times 100$ or $R_A = 0$.

Hence for designing 80 kHz oscillator, we select $C = 1 \text{ nf}$. So from equation (4), we get

$$80000 = \frac{1.44}{(R_A + 2R_B)C} = \frac{1.44}{(R_A + 2R_B)10^{-9}} \text{ or, } R_A + 2R_B = 18000$$

Since for 50 % duty cycle $R_A = 0$, so $R_B = 9000 \Omega = 9 \text{ k}\Omega$. In Practical circuit, the duty cycle may be selected slightly less than 50 %. So R_A is selected as variable $1 \text{ k}\Omega$ metal film 1 Watt potentiometer and R_B is selected as variable $10 \text{ k}\Omega$ metal film 1 Watt potentiometer. By adjusting the values of these potentiometers, 80 kHz pulsating signal is produced. The short circuited JK Flip-flop IC CD4027 divides this frequency by two and produces two 40 kHz signals of opposite phases at the output terminals. These 40 kHz signals are used to excite the transmitter probe (T_X) of storage tank through the buffer IC (CD4069) and capacitor C_2 which is selected

as 220 μf in order to block any d.c part present in the excitation signal.

The receiver circuit is designed by selecting the gain of the non-inverting amplifier using op-amp A_1 is selected at 20. So we have the gain equation,

$$20 = 1 + \frac{R_2}{R_1} \text{ or, } R_2 = 19R_1$$

Now R_1 is selected as 1 k Ω metal film half watt resistance with 1 % tolerance. Hence $R_2 = 19 \text{ k}\Omega$. So R_2 is selected as 22 k Ω metal film 1 Watt potentiometer with 5 % tolerance. For unity gain differential amplifier circuit with op-amp A_3 , $R_7 = R_8 = R_9 = R_{10}$ and each is selected as 1 k Ω metal film half watt resistance with 1 % tolerance. The other resistors $R_3 - R_6$ are also selected as 1 k Ω metal film half watt resistances each with 1 % tolerance. The zero adjustment potentiometer R_Z is selected as 22 k Ω , 1 Watt, and metal film linear potentiometers with 5 % tolerance. The op-amps A_1 , A_2 and A_3 are selected as low noise op-amp ICs OP-07. The diodes D_1 & D_2 are selected as IN 4148.

3.1. Accuracy Analysis

The accuracy of a transducer or any measuring unit may be determined from the measured output obtained by the repetition of the experiment for several times for the same input under the same environment in both increasing and decreasing modes as per IEC 61298-2 standard [2, 18]. From the repeated measured data, it is obtained from the zero deviation line or best-fit characteristic curve expressed in percentage of span or maximum range from the following equations.

$$\text{Measured accuracy} = \pm \frac{\text{Maximum (Best fit data-Measured data)}}{\text{Span}} \times 100\% \quad (14)$$

$$\begin{aligned} \text{Hysteresis plus dead band} \\ = \pm \left[\frac{\text{Maximum}[(\text{Measured data in increasing mode} - \text{Measured data in decreasing mode}) \text{ for the same input in one cycle}]}{\text{span}} \right] \times 100\% \end{aligned} \quad (15)$$

$$\text{Accuracy} = \pm \left(\frac{\text{Measured accuracy} + \text{hysteresis plus dead band}}{\text{span}} \right) \quad (16)$$

4. Experiment

The experiment was performed by using the experimental set up as schematically shown in Fig. 2 with its photographic view shown in Fig. 5. The proposed level transducer unit as shown in Fig. 2 and Fig. 5 consists of a storage tank provided with a gauge glass, an inlet valve V_1 and an outlet valve V_2 .

This tank may be filled up with tap water from an overhead tank through the inlet valve V_1 and may be

emptied through the outlet valve V_2 . The level of water in the tank at steady state can be measured from the position of water surface along the millimetre scale attached with the gauge glass.

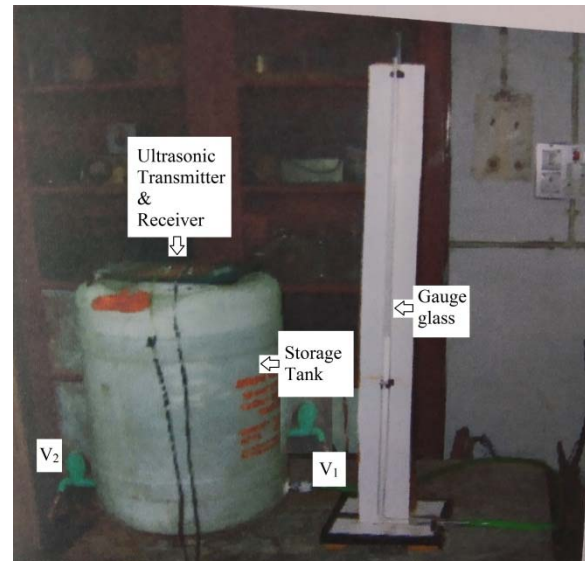


Fig. 5. Photographic view of the experimental set up.

To determine the static characteristic of the transducer, a particular level in the storage tank was selected as the datum level and by alternately opening and closing the inlet valve V_1 , the liquid level in the tank above the datum level was increased in steps and at each step the value of the transducer output was measured by a four and half digit multimeter and the corresponding liquid level above datum position was measured from the difference between the readings of the liquid surface position and the datum position along the gauge glass. From this value of level, the distance between the liquid surface and the receiver probe fixed on the cover plate was also determined from the difference between the maximum tank height and the reading of the liquid surface position along the gauge glass. Similarly by opening and closing of the exhaust valve V_2 , the liquid level was decreased in steps and at each step, the values of the transducer output, the liquid level and the distance between the liquid surface and the receiver probe were measured during performing the experiment in decreasing mode. The experiment was repeated for ten times in both increasing and decreasing modes at different dates and times under the same environment of an air-conditioned laboratory maintained at 25 °C. Now the static characteristic curves of the proposed transducer were drawn by plotting the transducer output against the distance between the liquid surface and receiver probe as shown in Fig. 6 (a). From these measured values of transducer output at a given level and at a given liquid surface-receiver probe distance, obtained during ten repetitions under the same laboratory environment, the average value of these transducer outputs was determined. Now the average static

characteristic curve of the transducer was drawn by plotting the average transducer output against the liquid surface-receiver probe distance as shown in Fig. 6(b). From this average static characteristic curve the best fit curve is drawn using Microsoft excel program along with the best fit characteristic equation as shown in the same figure. The percentage deviation of each measured average value from the best fit value is now determined and the percentage deviation curve of the transducer is drawn as shown in Fig. 6(c). Now at each level and liquid surface-receiver distance, the standard deviation (σ) of the measured data obtained in

ten repetitions is determined by using Microsoft Excel program. For each value of standard deviation, the percentage repeatability (r) of the measured data is determined by using the standard ASTM formula [18] given by, $r = 2\sqrt{2} \frac{\sigma}{\bar{X}_{\max}} \times 100\%$ where, $\bar{X}_{\max}$ is the

maximum average value for the transducer output. The repeatability curves for the proposed level transducer is now drawn by plotting the repeatability against the liquid surface-receiver probe distance as shown in Fig. 6(d).

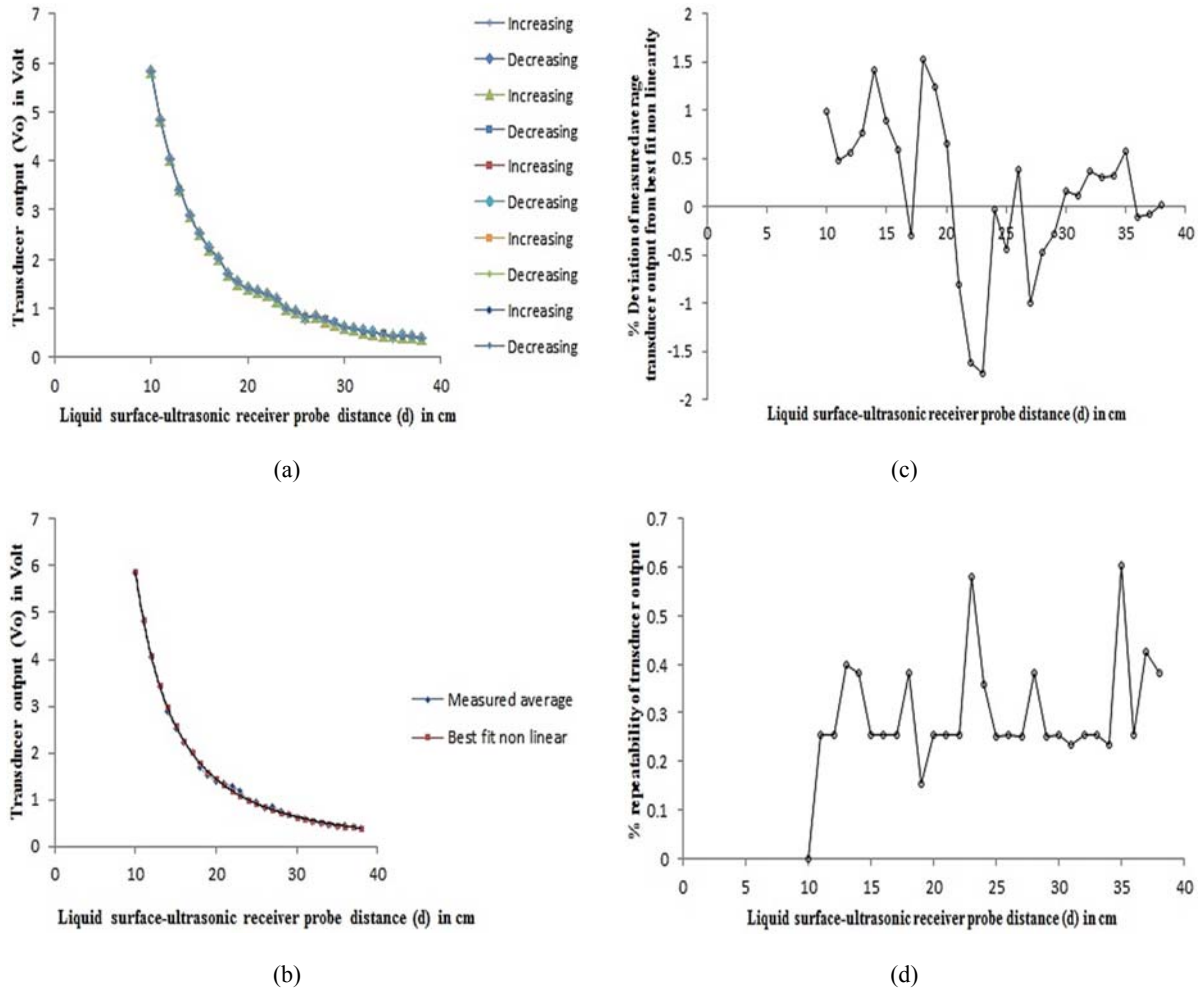


Fig. 6. Static characteristic curves of the proposed transducer with respect to the distance of reflecting water surface from the ultrasonic transmitter:

- Static characteristic curves of the proposed transducer for the measured data obtained from ten repetition in increasing and decreasing modes;
- Average static characteristic curve of the proposed transducer along with best fit characteristic and best-fit characteristic equation;
- Percentage deviation of the measured average static characteristic data from the corresponding best-fit data;
- Percentage repeatability of the measured data observed in ten repetitions.

5. Conclusions

The transducer static characteristic curves of the transducer obtained in ten repetitions of the experiment under the same laboratory environment at different dates and times as shown in Fig. 6(a) are all found to

be almost similar to the average static characteristic curve as shown in Fig. 6(b). The best fit characteristic equation as shown in Fig. 6(b) follows the derived equation (11) to a very good extent. The percentage deviation from the best fit non-linearity is also found to be very small as shown in Fig. 6(c). From the

percentage repeatability curve of the proposed level transducer as shown in Fig. 6 (d), the transducer is found to have good repeatability.

In the conventional non-contact ultrasonic liquid level transducer, the time of flight (TOF) between the instants of transmitting and receiving of the reflected ultrasonic wave from liquid surface of a storage tank is measured by a microprocessor or microcontroller or computer based technique. So the measuring unit is very costly but due to its various advantages such as very good linearity and good measurement accuracy, it is widely used in industry. But the proposed transducer technique is a simple intensity sensing technique and does not require any of the digital system associated with the conventional TOF technique. So the proposed level transducer technique involves much less cost than the conventional measuring unit. Its main disadvantage is that its output static characteristic is nonlinear. But this disadvantage can be easily overcome by using simple analog or digital linearization technique.

The measured accuracy, hysteresis plus dead band and overall accuracy of the proposed level transducer are calculated from the measured data in the repeated experiments under the same laboratory environment by using the standard equations (12), (13) and (14) respectively and are respectively, found to be $\pm 1.85\%$, $\pm 0.184\%$ and $\pm 2.034\%$. Thus the accuracy of measurement using the proposed level transducer is comparably good with respect to the conventional techniques as shown in Table 1.

Table 1. Comparative study of the measurement accuracy of the proposed level transducer with the conventional level transducers [2].

Type of transducer	Accuracy in $\pm$ % of span	Inference
Air bubbler type	0.5-1	The measurement accuracy of the proposed modified transducer is comparable with that of the conventional transducers
Capacitance type	0.5-3	
Diaphragm type	1-3	
Differential pressure type	0.25-1	
Displacer type	0.25-1	
Float type	0.1-3	
Radar type	0.1-1	
Nuclear type	1-2	
Resistance type	0.1-1	
Ultrasonic type	0.25-3	
Proposed modified ultrasonic type	2.034	

A good resolution of 1 mm was observed in the proposed flow transducer experiment because the level was measured from an mm scale. However, the proposed transducer was also found to respond to a very small change of level less than 1 mm. In industrial environment, an accuracy of 2.034 % of the liquid level measurement system is within acceptable limit and is comparable with the accuracy of some other techniques which may be as high as 3 %. The lack in

accuracy of the proposed technique may be due to the effect of atmospheric parameters like temperature, humidity etc. on the intensity of the ultrasonic signal. So a study of this effect is left as a future scope of the present work.

The conventional TOF type ultrasonic transducer output is dependent on the atmospheric parameters like temperature, humidity, etc. because for the liquid surface-receiver probe distance ($d = H-h$), $TOF = d / V = (H-h)/V$ is linearly dependent on level (h) only when the velocity (V) of sound wave is constant. Since the velocity of sound wave depends on these atmospheric parameters, the conventional ultrasonic flow transducer may suffer from measurement error. Now the intensity of sound wave is primarily dependent on the propagation distance along with the atmospheric parameters. But for a limited value of level in a storage tank, the effect of atmospheric parameters on the intensity of sound wave may be assumed to be negligible. Hence the error in level measurement by using the proposed technique due to the atmospheric parameters may be assumed to be smaller than that observed in the conventional technique.

It may be mentioned here that in the modern electronic era, the TOF type microcontroller based level or distance transducer IC like USTI, UFDC-1, UFDC-1M etc. are now easily available in the market at small cost. One disadvantage of this system may be mentioned as that it is not repairable. So in the present paper a simple low cost intensity sensing type technique has been proposed, which is repairable. The decrease of reliability due to use of more number of ICs may be overcome by selecting low noise op-amps like OP-07. In the proposed technique the effect of atmospheric temperature on the sound intensity has been ignored because the experiments have been performed repeatedly under the same environment of an air-conditioned laboratory maintained at 25 °C throughout a year. Since the air column collected over the liquid inside a storage tank is always saturated with the liquid vapor, so in the present work, the effect of humidity on sound intensity has not been considered. However, in industrial application, the effects of these atmospheric parameters as well as the signal frequency should be studied. This is left as a future scope of the present work.

Acknowledgements

The authors are thankful to the Department of Applied Physics, Instrumentation Engineering, University of Calcutta, and Saroj Mohan Institute of Technology, Guptipara for providing the facilities to carry out this work.

References

- [1]. Fraden J., Handbook of Modern Sensor, 3rd edition, AIP Press, Springer, 2003.

- [2]. Liptak B. G., Process Measurement and Analysis, 3rd edition, *Butterworth Heinman Ltd*, 1999.
- [3]. Considine D. M., Process Instruments and Controls Handbook, 2nd edition, *McGraw-Hill*, New York, NY, USA, 1999.
- [4]. Rocchi A., Santeccchia E., Ciciulla F., Mengucci P., Barucca G., Characterization and optimization of level measurement by an ultrasonic sensor system, *IEEE Sensors Journal*, Vol. 19, Issue 8, April 2019, pp. 3077-3084.
- [5]. Lasaygues P., Arciniegas A., Espinosa L., Prieto F., Brancheriau L., Accuracy of coded excitation methods for measuring of time of flight: Application to ultrasonic characterization of wood samples, *Ultrasonics*, Elsevier, Vol. 89, September 2018, pp. 178-186.
- [6]. Bello M. I., Gana S. M., Faruk M. I., Umar M. J., Autonomous ultrasonic based water level detection and control system, *Nigerian Journal of Technology (NIJOTECH)*, Vol. 37, June 2018, pp. 808-513.
- [7]. Zakaria Z., Idroas M., Samsuri A., Adam A., Ultrasonic instrumentation system for liquefied petroleum gas level monitoring, *Journal of Natural Gas Science and Engineering*, Elsevier Science Direct, Vol. 45, September 2017, pp. 428-435.
- [8]. Praher B., Steinbichler G., Ultrasound based measurement of liquid layer thickness: a novel time domain approach, *Mechanical Systems and Signal Processing*, Elsevier Science Direct, Vol. 82, January 2017, pp. 166-177.
- [9]. Petlach P., Dub M., Some aspects of COTS ultrasonic fuel level measurement, in *Proceedings of the IEEE International Conference on Military Technologies*, June, 2017, pp. 578-581.
- [10]. Li P., Chen S., Cai Y., Chen J., Li J., Accurate TOF measurement of ultrasonic signal echo from the liquid level based on a 2-D image processing method, *Neurocomputing*, Elsevier Science Direct, Vol. 175, January 2016, pp. 47-54.
- [11]. Li P., Cai Y., Chen X., Nabuzaale S., Yin J., Li J., An accurate detection for dynamic liquid level based on MIMO ultrasonic transducer array, *IEEE Transactions on Instrumentation and Measurement*, Vol. 64, Issue 3, March 2015, pp. 582-594.
- [12]. Suleiman M., Saidu G. I., Ilyasu M. I., Adeboye A. O., Hamza M., Ultrasonic fluid level measuring device, *International Journal of Recent Development in Engineering and Technology (IJRDET)*, Vol. 4, 2015, pp. 1-5.
- [13]. Licznarski T. J., Jaroński J., Kosz D., Ultrasonic system for accurate distance measurement in the air, *Ultrasonics*, Elsevier, Vol. 51, Issue 8, December 2011, pp. 960-965.
- [14]. Terzic J., Nagarajah C. R., Alamgir M., Fluid level measurement in dynamic environments using a single ultrasonic sensor and support vector machine, *Sensors and Actuators*, Elsevier Science Direct, Vol. 161, Issue 1-2, June 2010, pp. 278-287.
- [15]. Spatt W. K., Vetelino J. F., Lynnworth L. C., Liquid level torsional ultrasonic waveguide sensor, *IEEE International Ultrasonics Symposium Proceeding*, October 2009, pp. 663-668.
- [16]. Lee D. W., No H. C., Song C. H., Measurement of two-phase mixture level using an ultrasonic method, *Experimental Thermal and Fluid Science*, Elsevier, Vol. 29, Issue 5, June 2005, pp. 609-614.
- [17]. Maribout M., Habli M., Naamany A. A., Busaidi K. A., A new ultrasonic based device for accurate measurement of oil, emulsion, and water levels in oil tanks, in *Proceedings of the IEEE International and Measurement Technology Conference*, Vol. 3, May 2004, pp. 1942-1947.
- [18]. Sakharov V. E., S. A. Kuznetsov, S. A., Zaitsev B. D., Kuznetsova I. E., Joshi S. G., Liquid level sensor using ultrasonic lamb waves, *Ultrasonic*, Elsevier Science Direct, Vol. 41, Issue 4, June 2003, pp. 319-322.
- [19]. Vargas E., Ceres R., Marti'n J. M., Caldero'n L., Ultrasonic sensor for liquid level inspection in bottles, *Sensors and Actuators Elsevier Science Direct*, Vol. 61, Issue 1-3, June 1997, pp. 256-259.
- [20]. Gillespie A. B., Deighton M. O., Pike R. B., R. D. Watkins, A new ultrasonic technique for the measurement of liquid level, *Ultrasonics*, Elsevier, Vol. 20, Issue 1, January 1982, pp. 13-17.
- [21]. Jakevicius L., Demcenko A., Mardosaite R., Ultrasound attenuation dependence on air compression or expansion processes, *Ultragarsas (Ultrasound)*, Vol. 65, Issue 1, 2010, pp. 42-46.
- [22]. Yurish S. Y., Distance Measurement System Based on Ultrasonic Smart Sensors and Universal, Sensors and Transducers Interface (USTI), *Sensors and Transducers*, Vol. 243, Issue 4, August 2020, pp. 24-30.



Systematic Failure Detection and Correction in Environmental Monitoring Systems

^{1,*} Gonalo de JESUS, ¹ Anabela OLIVEIRA and ² Ant3nio CASIMIRO

¹ DHA-GTI, Laborat3rio Nacional de Engenharia Civil, Avenida do Brasil 101,
1700-066 Lisboa, Portugal

² LASIGE, Faculdade de Ci4ncias, Universidade de Lisboa, Campo Grande,
1749-016 Lisboa, Portugal

¹ Tel.: +3512184443422
E-mail: gjesus@lnec.pt

Received: 29 July 2021 /Accepted: 30 September 2021 /Published: 31 October 2021

Abstract: Sensor networks used in environmental monitoring applications are subject to harsh environmental conditions and hence are prone to experience failures in its measurements. Comparing to the common task of outlier detection in sensor data, we review herein the complex problem of detecting systematic failures such as drifts and offsets. Performing this detection in environmental monitoring networks becomes a stringent task especially when we need to distinguish data errors from real data deviations due to natural phenomenon. In this paper, we detail the scope of events and failures in sensor networks and, considering those differences, we introduce a new instantiation of a proven methodology for dependable runtime detection of outliers in environmental monitoring systems to address drifts and offsets. Lastly, we discuss the use of machine learning techniques to estimate the network sensors measurements based on the knowledge of processed past measurements alongside with the current neighbor sensors observations.

Keywords: Data quality, Failure detection, Sensor fusion, Machine learning, Sensor networks, Aquatic monitoring.

1. Introduction

When monitoring harsh environments, deployed sensors have to perform under unfavorable conditions, producing occasionally failures of several types. Measurements may be imprecise, incorrect, incomplete, incoherent or inappropriate to the problem at hand. Sensors may exhibit errors due to faults in sensors or other sources (e.g. communication), either being outliers, temporary disturbances or systematic deviations. These errors can ultimately contribute to the issuing of false warnings or wrong management decisions. We focus here on real environments subject to harsh conditions, namely aquatic environments.

Many of the existing techniques for fault detection do not consider the presence of natural phenomena interfering with sensor measurements [1, 2]. These phenomena can ultimately lead to deviations in measurements that might be wrongly perceived as errors. In this paper we consider physical phenomena as events, which are natural occurrences and their impact on measurements should not lead to wrongly detect faulty behaviors.

In the past decade there have been many studies supporting the use of machine learning techniques and sensor fusion to identify or classify events, including failure situations [3, 4]. The most common situations are related to faulty data observations due to spurious

errors, such as outliers or to communication faults or outliers derived from sensor faults. In fact, detection and mitigation techniques for drifts and offsets in the context of sensor networks have not been addressed thoroughly. Herein, we introduce a solution to detect and correct offsets and drifts, characterized by a systematic failure behavior observed during a determined time interval. These errors often occur when a sensor is functioning during a long period of time without intervention, requiring additional automated procedures to identify and correct faults in the measurements. In [5], we characterized a methodology that uses prediction methods and failure detection techniques in order to promote the identification of failure behaviors in sensor measurements.

Herein we propose an instantiation of the methodology presented in [6], comprising machine learning strategies for the prediction of the expected sensor measurements of each sensor node, but now accounting only for faults related to drifts and offsets.

This paper is organized as follows. In Section 2, we identify related work on mechanisms and techniques for detecting offsets and drifts, including the use of data fusion strategies. In Section 3 we briefly overview the base methodology and in Section 4 we describe the proposed instantiation and assumptions required for the application for drifts and offsets detection.

2. Related Work

Methods for detection and correction of drifting and offset failure behaviors in sensor devices are different for single device and multiple devices (network). In the first category, we discuss calibration and its variants as a process to prevent and correct such failures. In contrast, in a multi-sensor situation, it is possible to use data fusion techniques in order to detect and correct drifts and offsets.

The re-calibration process of sensors is usually performed off-field by removing the sensor of the monitoring environment and recalibrating it in controlled conditions, with potential data loss if no redundant way of collecting sensor data is available (and the added re-deployment costs).

Although sensor calibration may be sometimes a costly operation, given its frequency, it is necessary to assure the maintenance of good quality data. In order to minimize the number of interventions in the sensor, a possible alternative is the auto or self-calibration, which is a software-based procedure to enable sensors to monitor themselves and self-calibrate using a reference. This latter option, being adaptive, is potentially better to deal with varied and even unpredicted circumstances, and is also designated as measurand reconstruction or sensor compensation.

The auto-calibration process is referred to the methods aimed at diminishing the effect of the disturbing parameters in the features of sensors. The sensor becomes less sensible to past information,

interfering environmental factors and noise. This is possible via numerical techniques that compensate the disturbances. These techniques are applied after the transformed signal being quantified, through digital signal processing. This method has been used with relative success, for instance exploiting statistical regression based on a priori knowledge [6] or using artificial neural networks [7, 8].

For the multi-sensor scenario, particularly in the context of sensor networks, these automatic calibration techniques have also been studied to correct drifts and offsets failures. However, these techniques only consider blind calibration, which means that there are no detection mechanisms for data faults. One of the first works is presented in [9], where the authors designed an algorithm to be used in high-density sensor networks in a post-deployment phase. This algorithm uses temporal correlations between pairs of neighbor sensors to correct their signal (measurements). An additional phase of the algorithm, particularly useful in the context of multi-sensor networks, is explained as an optimization step by dealing with groups or clusters of sensor nodes.

Balzano, *et al.* [10] deals with blind calibration in sensor networks softening the high-density requirement, assuming a linear model for the sensor calibration functions, meaning that sensor readings are calibrated up to an unknown gain and offset for each sensor. They too rely on sensor correlations to model their behavior. In fact, data fusion is a common subject in blind calibration studies (more examples in [11-13]).

For the single sensor networks scenario, there is a limited number of studies considering both detection and correction mechanisms of offset and drifts failures. Offsets analyses are more common than drifting ones, in particular in applications related to digital imagery. One exception is [15], where the authors present a machine learning approach to detect offset and drifts faults in WSNs. Their method consists in using Hidden Markov Models to capture both the dynamics of the environment and the dynamics of the faults. This work also presents an analysis on the extracted models to determine the types of faults (including offsets) affecting the sensor measurements.

Concerning specifically drifting failures, a research group presented several studies over the last years regarding a design and its various improvements of a drift-aware sensor network [15-24]. The original study presented the concept of a mechanism to detect and correct drifts in sensor networks. Afterwards, several data fusion techniques were introduced and demonstrated to be efficient. The group used statistical techniques, Kalman filters, Interacting Multiple Model algorithm, Recursive Bayesian algorithm, Spatial Kriging method, and ensembles of these techniques. Their work has been applied to high-density sensor networks measuring parameters such as temperature but also to image-related networks with geospatial information. Provided results in indoor sensor networks have proved the methods to be quite successful in detecting and correcting drifts and offsets

in the range of (-10,10) added to the sensor measurements, presenting root mean square errors in the range of (5,8).

Lastly, focusing simply on the detection mechanism, [25] presents a fault detection method for WSNs based on a multi-scale Principal Component Analysis (MSPCA), applied in a laboratory network dataset, the same as the previous studies, to detect both offsets and drifts failures for temperature sensors. The provided results prove that the method is effective in detecting artificially injected systematic faults of different magnitudes and time duration.

Although these last studies have promising results in the field of detecting drifts and offsets in sensor measurements, their focus is mostly in laboratory or indoor conditions. Their methods do not consider the high variability of environmental monitoring, which we take in consideration in the methodology presented in [5].

3. Methodology Overview

A methodology for processing measurements from multiple sensors is proposed in [5]. This methodology addresses failure detection, data quality assessment and data correction applied to outliers. The methodology is mostly intended to be applied during runtime, for the detection of faulty measurements and the respective mitigation in a continuous way, during the sensor operation.

The purpose of the methodology is not only to detect failures in measurements but also to characterize the quality of each measurement and if this quality is below some threshold, be able to provide an estimation of a replacement measurement with better quality. Therefore, a solution for dependable data quality needs to encompass the decision-making capabilities of a classifier in order to detect faulty measurements, as well as the prediction mechanisms to model the sensors behaviors to estimate expected values for the measurements. However, this classification does not necessarily need to be based on machine learning approaches. Therefore, for the purpose of defining a generic methodology, both types of capabilities, that is, detection and estimation, are necessary.

The methodology encompasses the use of prediction methods to estimate the expected sensors measurements, which in practice exploit machine learning techniques. It also encompasses failure detection but the concrete techniques to implement failure detection may not be based on machine learning.

We defined it to be generally applicable to any WSN monitoring system in harsh environments. This is accomplished by defining essential functionalities. The described methods are proposed independently of the physical processes being monitored, but leaving room for the selection of methods whose results depend on the concrete behavior of the monitored processes.

A sensor network architecture composed of more than 1 sensor nodes is assumed where each node is equipped with one or more sensors measuring different, but correlated physical processes. Sensor nodes may be physically distant, but their measurements are also correlated. The network has a gateway or sink node that receives all sensor measurements, although we do not consider a specific network topology. The sink node is responsible for processing sensor measurements using the proposed methodology, making the dependable monitoring data available to other systems upstream.

Regarding temporal aspects, sensor nodes are assumed to be configured to periodically transmit a new measurement, but no assumption is made on the frequency of transmission nor on the synchronization between different sensor nodes. Message transmission delays are assumed to be negligible in comparison to the dynamics of the monitored physical processes. Furthermore, all measurements received at the sink node are considered to be assigned the timestamp obtained from its local clock, allowing temporal correlations between independent measurements to be considered by the processing methods. The local clock at the sink node is assumed to be correct.

Regarding the assumed fault models, there is a specific focus on sensor data with outliers, drifts and offsets, regardless the nature of these value faults. The handling of omissions (i.e., sporadic loss of a measurement) and the crash of sensor nodes are also considered, as well as recovery of lost information. For crash failures, however, this recovery is only partial.

The methodology requires several models to characterize the correct behavior of each sensor, composed of one or more supervised learning techniques. A preliminary step is to construct these models, which requires sensor data with absence of measurement errors from all the sensors to be used. The models will explore temporal correlations between consecutive past measurements of the target sensor, spatial and value correlations between past measurements of the target sensor and past measurements from a variable number of other sensors. Spatial correlations are used when the target sensor and other sensors are in different geographical locations. Value correlations exist for example between the target sensor and sensors placed at the same location.

Consequently, the methodology is designed as an ensemble of supervised learning methods, which require an offline initial training phase for each node's model construction.

The methodology is composed of 4 blocks that are executed for each new received measurement from each target sensor. The first block is the Prediction (P) block, where we employ prediction methods in order to get one or more estimates of the measurement expected to be obtained from the target sensor.

The second block is the Failure Detection (FD) block, which objective is to identify possible failure behaviors in the target sensor dataset, through

procedures that help identify if a measurement is considered normal or abnormal, contemplating that these anomalies can be caused by a real environmental event and not a sensor fault.

The third block is the Quality Evaluation (QE) block. It determines the quality coefficient for the measurement and characterizes it whether it is faulty or not, setting the coefficient from 0 to 1.

The fourth and last block is the Measurement Reassessment (MR) block, where a replacement for a faulty measurement is estimated using as input the predictions in the Prediction block.

A flow diagram of the 4 blocks of the methodology is provided in Fig. 1.

The proposed methodology was evaluated and validated by instantiating it for the particular scenario of outliers detection and correction [5]. Firstly, we developed a solution according the methodology to detect outliers in an aquatic monitoring system in the Columbia River (Oregon, USA). Lastly, this instantiation was further compared with other state-of-the-art solutions in a benchmark case study for indoor monitoring, proving its validity by performing at least as good as the best solution in the comparison study.

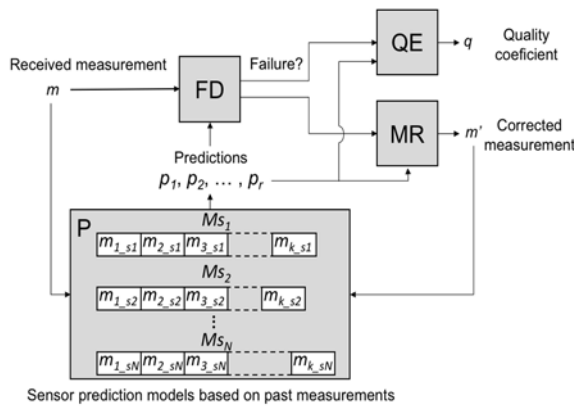


Fig. 1. Flow diagram of the methodology.

4. Systematic Failures Solution

4.1. Objectives

In monitoring networks, solutions for failure detection and mitigation need to aim not only to the more popular spurious failures as the outliers, but also the less frequent scenarios of offsets and drifts.

Another important concept considered in the methodology is the capability to distinguish the sensor faults from the environment-related events. These events can be perceived by the fault detection mechanisms as failures, which in this case are indeed false positives. To avoid this problem, we start by defining both events and failures as we comprehend them in our study.

We characterize events as the physical phenomena that impact the monitored environment to some extent. These can be of short duration or long lived like for

instance heavy rain or incrustation of marine life in the sensors. All such events are difficult to predict, and may affect the sensors measurements. We consider that an event has a wide scope and it is not just a localized happening. For instance, an object collision with a sensor is a short-lived happening that may produce a sensor fault (possibly causing an outlier). The presence of animals in contact with or attached to a sensor's structure is an example of a long-lived fault (in this case possibly causing an offset error).

Furthermore, events may lead to deviations from expected values in measurements that may be wrongly perceived as faults. We want to distinguish between events and faults. Therefore, because according to our definition, events have a wide scope, we can exploit spatial redundancy to deploy multiple sensor nodes that will allow us to determine when unusual measurements are consistently observed and hence report an event. In a natural environment, as considered herein, the range of events is very wide and heterogenous. It is very hard to define all specific event signatures which could help to detect the events and differentiate them from faults. Therefore, the application of our methodology to offsets and drifts detection in these environments considers localized events as a fault.

In the aforementioned methodology, we use redundancy and we compare several measurements in order to derive conclusions from these comparisons. If the sensor is performing as expected, which can be determined by analyzing the data produced by the sensor using data processing methods, then it is considered to be in a normal state. If the data processing method detects the existence of some anomalous measurements, then it is said to be in a failure state. Finally, it is possible that these anomalous measurements are also observed in the output of all other related sensors. In this case, all the sensors are in an event state. Otherwise, we need to reason in terms of the majority of observations. If the majority of the related nodes produce measurements showing anomalies, then the network is in an event state. Otherwise, the network is in a normal state and the minority of nodes that are not performing as expected are in a failure state.

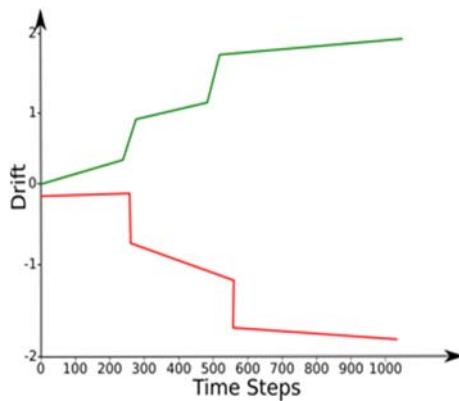
The above definitions become particularly relevant when exploring the spatial correlations between neighbor sensors in order to correctly identify both the event and the failure behavior [26]. More importantly, these are the foundations for the implementation of the solution for systematic failures.

For the instantiation of the methodology to the detection and correction of systematic failures such as drifts and offsets, we follow the same techniques as the ones presented in [5] for the outlier setup strategy (ANNODE), namely artificial neural networks (ANNs) and statistical techniques respectively used in the Prediction and Failure Detection blocks of the methodology. However, since there are notorious differences between spurious and systematic errors, these have implications on the strategies for Prediction and Failure Detection blocks. Indeed, the procedures

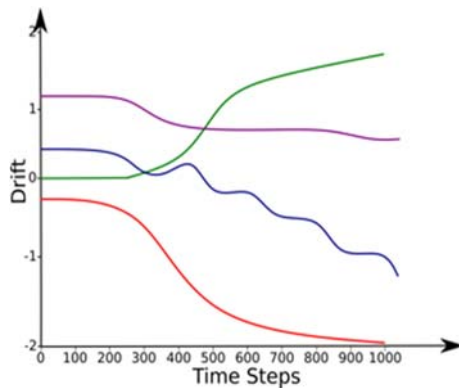
and techniques need to be customized specifically for failures that show a persistent behavior over a time interval.

4.2. Systematic Failures

Offset failures can be characterized by a period of time during which the measurements exhibit a given offset, constant or almost with no variance, with respect to the expected sensor readings. It is the behavior shown during a time interval that provides the systematic aspect, different from the spurious behavior of an outlier. On the drift failures, the drifting behaviors can be split into two categories related to their general pattern. A drift can be characterized by a smooth and slowly decay or growth, as in a linear or exponential function, represented in Fig. 2(a). The second category describes a drift also with a linear or exponential decay or growth but presenting discontinuities or sudden surges, abrupt changes or accentuated peaks, represented in Fig. 2(b).



(a)



(b)

Fig. 2. Categories of Drifting failures:
a) Sharp drifts; b) Smooth drifts.

4.3. Prediction Block

A solution for the detection and correction of offsets and drifts should follow three steps. First, in a

sensor network there must be a selection of the network sensor nodes that are highly likely to be correlated. This correlation can be verified by considering either the physical distance or through expert knowledge of the specific environment dynamics.

The second step is the selection of the data fusion techniques for the Prediction (P) block, considering that such techniques must be adequate to resolve the estimation problem (predicting the target sensor next measurement). Finally, the third step includes the selection of the specific datasets for the training process (if required) of the chosen techniques.

We defined the type and structure of ANNs to use for the datasets of a case study [5], in which for monitoring measurements of a given target sensor, the inputs are comprised of the vectors with a history of measurements of the neighbor sensors and possibly of the target sensor itself. Regarding the layer structure, besides the input and output layers, the ANNs are composed also with two hidden layers. The ANNs output is trained to be a prediction of the target sensor next measurement (single value).

In terms of the predictions provided by the ANNs (P block), there is a clear difference between outlier and systematic detection. For systematic failures detection prediction models based on the target past measurements are not considered.

Consequently, we only consider ANNs trained based on the measurements of the neighbor sensors. Therefore, we discard past measurements from the target sensor because these have a strong influence in the predictions and could lead to wrong predictions.

One important difference between systematic and spurious errors is that in the former, they are observed over time while the latter are observed in a single measurement. Therefore, systematic errors cannot be detected as soon as they start, only after being observed for a certain time interval.

Another important aspect to consider for the specific situation of environment monitoring networks is that the sensors are widespread in space, which may diminish the prediction techniques accuracy. Moreover, without explicit sensor redundancy where we have at least two sensors in the same place (location), we are likely to have less accurate estimations for the target sensor measurement. Therefore, in order to obtain a more complete view of the monitoring system, we are required to have several correlated neighbor sensors.

4.4. Failure Detection Block

In the Failure Detection (FD) block, similarly to the outlier detection ANNODE solution [5], we consider a statistical technique as a comparison method, in order to calculate the differences between each measurement and the corresponding predictions provided by the Prediction block (P). This statistical technique uses a training dataset to learn the probability distributions fittings between the errors of

the prediction models defined in P and the expected measurements. Using the training dataset, the square errors between the measurement and each prediction are obtained and we are able to obtain the final cumulative density function (CDF). This CDF allows us to calculate the probability of the error between current target sensor reading and prediction. Therefore, by defining a threshold for error probability, we can assess the significance of the observed differences between the measurement and the predictions.

In this solution for the detection of systematic errors, we have different detection conditions from those formulated in ANNODE. Firstly, each measurement of the target sensor is compared with the predictions. The number of significant differences, which can be between zero and total number of predictions, is then recorded. Afterwards, these differences are evaluated over a significant temporal window to perform the intended detection of systematic failure.

For this systematic detection, a temporal window must be defined so we can distinguish single point situations from systematic failures or even from an environment-related event. These single point situations can be spurious errors or just regular fluctuations in the differences between the measurement and the corresponding predictions, in which the difference can be significant for that instant but not in a systematic manner. This temporal window will allow us to characterize correctly a systematic failure, either being an offset or a drift.

The temporal window will have user-specified, pre-defined time units, which is typically defined by the application and related with the required failure detection latency. The rule of thumb is that the window must include enough measurements to characterize the temporal scales of relevance with enough resolution for the phenomena at stake, depending also on the frequency of sensor measurements. The number of measurements in the window must be at least 3, such that it is possible to conclude that a certain behavior is systematic, but it can be made larger as this will allow more precise conclusions.

5. Conclusions

We propose herein a new approach for drift and offset behaviors detection, specifically targeted for application in environmental sensor networks. The implementation is based on an instantiation of a past methodology [3], applicable to short- and long-term failures. The new methodology comprises relevant prediction models for the next measurement of the target sensor, using machine learning techniques based only on the neighbor's information. The next steps will be to demonstrate it with real world data, in a complex environment setting.

Acknowledgements

This paper is part of the work of project AQUAMON (PTDC/CCI-COM/30142/2017), funded by the Fundação para a Ciência e a Tecnologia (FCT).

References

- [1]. E. W. Dereszynski, T. G. Dietterich, Spatiotemporal models for data-anomaly detection in dynamic environmental monitoring campaigns, *ACM Transactions on Sensor Networks (TOSN)*, Vol. 8, Issue 1, 2011, pp. 1-36.
- [2]. V. Garcia-Font, C. Garrigues, H. Rifà-Pous, A comparative study of anomaly detection techniques for smart city wireless sensor networks, *Sensors*, Vol. 16, Issue 6, 2016.
- [3]. M. Bahrepour, N. Meratnia, M. Poel, Z. Taghikhaki, P. J. Havinga, Distributed event detection in wireless sensor networks for disaster management, in *Proceedings of the International Conference on Intelligent Networking and Collaborative Systems*, 2010, pp. 507-512.
- [4]. Y. Singh, S. Saha, U. Chugh, C. Gupta, Distributed event detection in wireless sensor networks for forest fires, in *Proceedings of the UKSim 15th International Conference on Computer Modelling and Simulation*, 2013, pp. 634-639.
- [5]. G. Jesus, A. Oliveira, A. Casimiro, Using Machine Learning for Dependable Outlier Detection in Environmental Monitoring Systems, *ACM Transactions on Cyber-Physical Systems*, Vol. 5, Issue 3, 2021, pp. 1-30.
- [6]. K. Whitehouse, D. Culler, Calibration as parameter estimation in sensor networks, in *Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications*, 2002, pp. 59-67.
- [7]. J. C. Patra, P. K. Meher, G. Chakraborty, Development of Laguerre neural-network-based intelligent sensors for wireless sensor networks, *IEEE Transactions on Instrumentation and Measurement*, Vol. 60, Issue 3, 2010, pp. 725-734.
- [8]. J. Rivera, M. Carrillo, M. Chacón, G. Herrera, G. Bojorquez, Self-calibration and optimal response in intelligent sensors design based on artificial neural networks, *Sensors*, Vol. 7 Issue 8, 2007, pp.1509-1529.
- [9]. V. Bychkovskiy, S. Megerian, D. Estrin, M. Potkonjak, A collaborative approach to in-place sensor calibration. *Information Processing in Sensor Networks*, 2003, pp. 301-316.
- [10]. L. Balzano, R. Nowak, Blind calibration of sensor networks, in *Proceedings of the 6th International Conference on Information Processing in Sensor Networks*, 2007, pp. 79-88.
- [11]. J. Feng, S. Megerian, M. Potkonjak, Model-based calibration for sensor networks, *IEEE Sensors*, Vol. 2, Issue 2, 2003, pp. 737-742.
- [12]. R. Tan, G. Xing, X. Liu, J. Yao, Z. Yuan, Adaptive calibration for fusion-based cyber-physical systems, *ACM Transactions on Embedded Computing Systems (TECS)*, Vol. 11, Issue 4, 2013, pp. 1-25.
- [13]. Y. Wang, A. Yang, Z. Li, X. Chen, P. Wang, H. Yang, Blind drift calibration of sensor networks using sparse Bayesian learning, *IEEE Sensors Journal*, Vol. 16, Issue 16, 2016, pp. 6249-6260.

- [14]. E. U. Warriach, M. Aiello, K. Tei, A machine learning approach for identifying and classifying faults in wireless sensor network, in *Proceedings of the IEEE 15th International Conference on Computational Science and Engineering*, 2012, pp. 618-625.
- [15]. M. Takruri, S. Challa, Drift aware wireless sensor networks, in *Proceedings of the 10th International Conference on Information Fusion*, 2007, pp. 1-7.
- [16]. M. Takruri, S. Rajasegarar, S. Challa, C. Leckie, M. Palaniswami, Online drift correction in wireless sensor networks using spatio-temporal modeling, in *Proceedings of the IEEE 11th International Conference on Information Fusion*, 2008, pp. 1-8.
- [17]. M. Takruri, K. Aboura, S. Challa, Distributed recursive algorithm for auto calibration in drift aware wireless sensor networks, *Innovations and Advanced Techniques in Systems, Computing Sciences and Software Engineering*, 2008, pp. 21-25.
- [18]. M. Takruri, S. Challa, R. Chakravorty, Auto calibration in drift aware wireless sensor networks using the interacting multiple model algorithm, in *Proceedings of the IEEE Mosharaka International Conference on Communications, Computers and Applications*, 2008, pp. 98-103.
- [19]. M. Takruri, S. Challa, R. Yunis, Data fusion techniques for auto calibration in wireless sensor networks, in *Proceedings of the IEEE 12th International Conference on Information Fusion*, 2009, pp. 132-139.
- [20]. M. Takruri, S. Challa, R. Chakravorty, Recursive bayesian approaches for auto calibration in drift aware wireless sensor networks, *Journal of Networks*, Vol. 5, Issue 7, 2010, pp. 823-832.
- [21]. M. Takruri, S. Challa, Data Fusion Approach for Error Correction in Wireless Sensor Networks, *Wireless Sensor Networks: Application-Centric Design*, 2010, 353.
- [22]. D. Kumar, S. Rajasegarar, M. Palaniswami, Automatic sensor drift detection and correction using spatial kriging and Kalman filtering, in *Proceedings of the IEEE International Conference on Distributed Computing in Sensor Systems*, 2013, pp. 183-190.
- [23]. D. Kumar, S. Rajasegarar, M. Palaniswami, Geospatial estimation-based auto drift correction in wireless sensor networks, *ACM Transactions on Sensor Networks (TOSN)*, Vol. 11, Issue 3, 2015, pp. 1-39.
- [24]. P. Rathore, D. Kumar, S. Rajasegarar, M. Palaniswami, Bayesian maximum entropy and interacting multiple model based automatic sensor drift detection and correction in an IoT environment, in *Proceedings of the IEEE 4th World Forum on Internet of Things (WF-IoT)*, 2018, pp. 598-603.
- [25]. Y. Xie, X. Chen, J. Zhao, Data fault detection for wireless sensor networks using multi-scale PCA method, in *Proceedings of the 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC)*, 2011, pp. 7035-7038.
- [26]. N. Peng, W. Zhang, H. Ling, Y. Zhang, L. Zheng, Fault-tolerant anomaly detection method in wireless sensor networks, *Information*, Vol. 9, Issue 9, 2018, pp. 236.
- [27]. G. Jesus, A. Oliveira, A. Casimiro, Detecting Drifts and Offsets in Environmental Monitoring Networks, in *Proceedings of the 7th International Conference on Sensors and Electronic Instrumentation Advances (SEIA'2021)*, Palma de Mallorca, Spain, 2021, pp. 97-101.



Published by International Frequency Sensor Association (IFSA) Publishing, S. L., 2021
(<http://www.sensorsportal.com>).

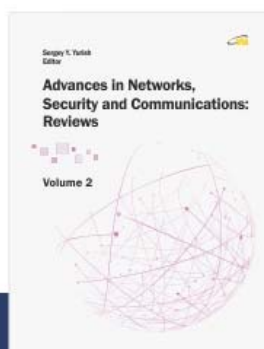
Your chapter may be in the next volume of the

Advances in Networks, Security and Communications: Reviews

Open Access Book Series



http://www.sensorsportal.com/HTML/IFSA_Publishing.htm



Simulation and Measurement of Comfort Related Microclimate

¹Michael Kurz, ²Christoph Russ and ¹Bernhard Kurz

¹Institute for Applied Ergonomics, Siedlerstr. 1, 85716 Unterschleissheim, Germany

²InsideClimate GmbH, Hilpoltsteinerstr. 1b, 83607 Holzkirchen, Germany

¹Tel.: + 49 89 62489595, fax: + 49 89 662065

E-mail: info@ifaerg.de

Received: 9 August 2021 /Accepted: 29 September 2021 /Published: 31 October 2021

Abstract: Although microclimate is only one aspect when it comes to look at comfort determining factors, it decisively gains importance with increased wearing or using cycles of apparel, seating and laying systems. One of the challenges arising with validation of climate comfort are suitable test and evaluation standards in order to achieve high reproducibility and reliable forecasts. These requirements can only be met economically with human-physiologically adapted climate simulation combined with a suitable measuring technique for temperature and humidity distributions. The unique combination of the SWEATOR climate simulation and the SWEATlog sensor mats meet this requirements in an outstanding way. Apart from realistic and physiologically relevant microclimate simulations, the application of special, precise and bus-compatible combi-sensors for temperature and humidity offers the calculation of heat and humidity maps for visualization. Using specific clustering methods and numberless correlation results from occupant tests, the calculation of various material parameters, such as thermal or vapor resistances, as well as comfort indicators can be realized for valuable and reliable comfort forecasts.

Keywords: Microclimate measurement, Heat and humidity map, Microclimate simulation, Comfort assessment.

1. Introduction

Many products in our day to day live are assigned to be ergonomical and comfortable with high usability and conformity. Especially for apparel, seats and mattresses we have learned, that they should be breathable, waterproof and climate managing. But how can these attributes be assessed and what is the importance respectively the true advantage for the user?

Regarding the climate comfort in particular the physiological requirements of the thermoregulation as well as the individual sensations have to be analyzed. When humans are asked, whether they prefer warm or cool respectively dry or humid climate, the answers indicate a clear preference for dry. Warm or cool remains to be evenly distributed. This is although

humans do not have any moisture receptors. Hence the concept of warm or cold sensations must be a combination of heat and humidity developments. This confirms the slogan “some like it warmer, some colder, but all prefer dry!”. So how does a moisture sensation arise and what role does the temperature and humidity level play for a comfort perception? Which measurement technology enables the quantification of this comfort aspect, which is one of the decisive factors for product quality?

2. Comfort

When searching for a meaningful description of comfort, a simple but also extremely appropriate

formulation may be: comfort is not just less but no uncomfortable perception at all. So it seems to be better to have a look at discomfort instead of comfort.

Example: Wearing new shoes the first times will generate pressure points, tight sensations, warm and humid perceptions and local skin irritations, often resulting in red skin or even blisters. Consequently comfort has a biomechanical as well as a climatic proportion, whereas the perception of discomfort is primarily determined by biomechanical aspects, which are complemented and maybe even overruled by climatic factors with increasing wearing times. The decisive point of a climate comfort view reveals within the resulting microclimatic conditions, quantified by temperature and humidity.

In practice many investigations on general climate comfort have been published. The majority sets focus on various ambient temperature, humidity and air flow, even radiation, resulting in recommendations of comfortable and uncomfortable areas or zones depending on workloads and clothing situations (see Fig. 1) [3, 4, 5, 15].

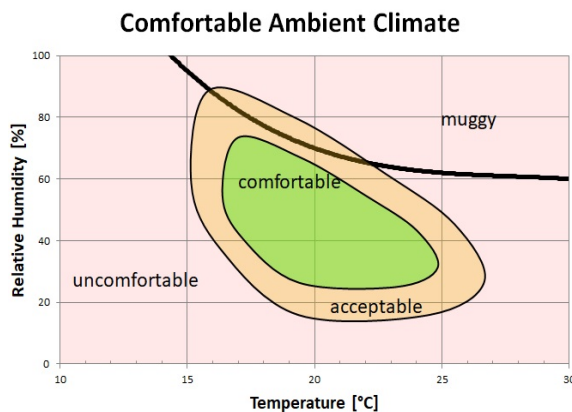


Fig. 1. Areas of comfortable and uncomfortable perception for environ's climates under certain clothing and physical situation.

Such information on general climate comfort however disregard the fact, that regional discomfort conditions have a decisive influence on the resulting perception of general comfort. Coming back to the example with the shoes, imagine that you are waiting for the bus in winter, wearing warm clothing, but standing in the slush, shoes are wet and feet are cold. It becomes obvious that this regional discomfort in the feet area will mainly influence and maybe overrule the general comfort perception (see Fig. 2).

This aspect of regional discomfort has been investigated barely and results are just available for feet, hand and seat/backrest region [1, 9, 14].

To understand the central role of microclimate on the comfort perception, a look at human thermophysiology will help. Its goal is the production of heat to stabilize the core temperature at about 37 °C. According to thermal or physical load this heat production will vary. In case of too much heat the

necessity of discharge will increase, otherwise heat loss is decreased and additional heat production (trembling) will start. Heat loss is physiologically controlled by a change of blood circulation and, in particular the increase, also by evaporation. In both cases the clothing system should assist the thermoregulation by adjusted isolation respectively heat and humidity transmission. These mechanisms will change the temperature and humidity in the microclimate of the boundary layer between skin surface and textile.

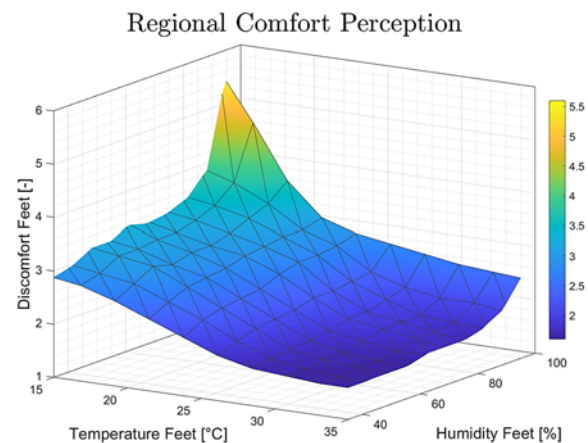


Fig. 2. Local discomfort perception in the feet sector for various microclimates in the shoe.

Based on many trials with human occupants on seats, in beds, and with diverse apparel products the human thermoregulation behavior measured as the microclimate close to the skin can be separated into three phases (see Fig. 3):

Phase 1: thermal neutrality, characterized by:

- Low temperature changes with up to ± 1 °C within the comfort range 31.5 °C – 35.5 °C.
- The heat balance is even, sweating as active body own method to influence the heat only happens in little doses (fine tuning).

- Dynamic regulating activity of low sensitive perspiration with slightly upward and downward developing absolute humidity levels occur, which over time do not accumulate in the human/textile interface.

Phase 2: Tendency to feel cold, characterized by:

- Decrease of the skin temperature below the comfort zone, risk of a reduction of the body core temperature.

- Demand for heat supply increases. Sensitive (active) sweating shuts down; humidity gradients decrease or remain stable.

- Lowest sweat emission, only insensitive sweating with very little absolute humidity and low to zero dynamic.

Phase 3: Tendency to overheat and sweat, characterized by:

- Increasing skin temperature over the comfort level, increasing tendency of the body core temperature.

- The demand for heat release increases; growing sweat activity with higher upward trends of humidity levels.

- In the measurable view a medium to high accumulating absolute humidity in textile layers can be seen.

Thus, the decisive conclusion from the measured assessment of climate comfort is to focus on the directly developing microclimate at the human/textile interface providing kind of a blueprint of the thermoregulation processes [11].

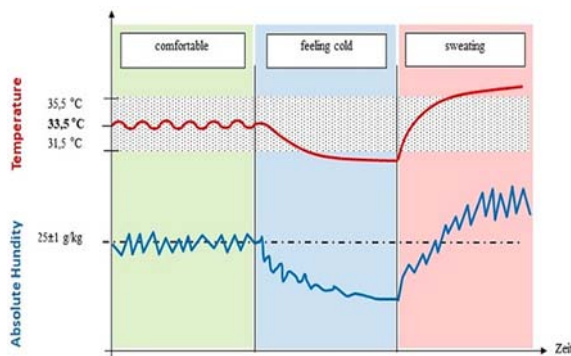


Fig. 3. Characteristics of thermoregulative phases.

To close the gap between measured microclimate and occupant's perception specific investigations have been conducted with the confirming result: microclimate is the best matching indicator for climate comfort by close correlation to perception. (Fig. 4).

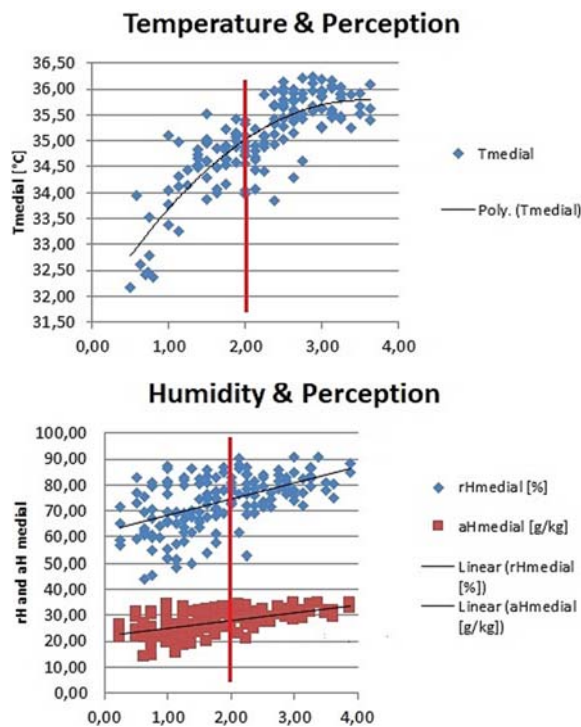


Fig. 4. Combined temperature and humidity perceptions of proband tests in shoes under various climate and physical stress conditions.

Fig. 4 shows the perception scores for various microclimate situations in the feet section as well as possible regressions to the measured values:

- Very good fitting of perceived heat to measured temperature;

- Weak correlation between measured relative humidity and their perception;

- and best between the comfort perception and absolute humidity, which combines relative humidity and temperature.

But Fig. 4 visualizes also a widespread diversity between the individuals. To get reproducible and valuable results many occupants and many tests are necessary, what is cost and time consuming. This justifies a standardized heat and humidity source.

3. Simulation of Microclimate

As a consequence of the standardization demands for climate tests artificial systems are applied. Those emit heat and humidity aiming to measure and calculate physical material parameters such as heat conduction and vapor transmission respectively storage. Others aim to simulate the human heat and humidity emission (thermoregulation) creating a certain microclimate with the test object, which allows a reliable prediction of the climate comfort [2, 6, 10, 12]. Such climate dummies can be found either as whole-body manikins or formed as single body parts. They are mostly of highly complex technology and sometimes come with instable processes. Standards have been available for decades like Sweating Guarded Hotplate (SGHP) respectively Hohenstein's Skin Model [16] but without a focus on microclimate.

Apart from standardized test conditions, e.g. ambient climate, measurement spots and sensor quality, the particular challenge for the setup and operation of such climate simulation systems is the best possible replication of the physiological human evaporation and the combination of heat and humidity emissions. Only this way defined climatic conditions and energy rates will ensure realistic heat and moisture flows and stationary microclimate situations.

According to the necessary features of a standardized heat and humidity source the SWEATOR system has been developed [7]. This technology is based on a water-filled, heat controlled hollow body with a special water vapor permeable membrane coating. The test specimens can be manufactured in different shapes (see Fig. 5), with different permeable membranes and without or with different surface perforations. The heating and water circulation are controlled by a touch screen control unit. Energy inputs from a few Watts to 400 W per square meter and sweating rates between 50 and 600 ml/m²×h are possible. For human physiological simulations under normal conditions, settings of 30 - 50 W/m² or 90 - 120 ml/m²×h are used. After pre-conditioning the device to the desired values, the SWEATOR manikin is applied to the confectioned test objects. In the boundary layer between SWEATOR surface and

material probe the microclimate distribution is measured with single sensors resp. a sensor array at defined locations (see chapter 4). The test trials take place under climatically defined room conditions including additional convections, if necessary. The SWEATOR technology thus enables realistic test conditions and non-destructive testing options with ready-made products.



Fig. 5. SWEATOR torso with test jacket, SWEATOR foot and SWEATOR head with safety helmet.

The SWEATOR control unit records and stores the supplied energies, weight changes and microclimate conditions even within various textile layers or outlets of ventilation channels.

Regarding the thermal system self-loss, the moisture quantity, stored in the sample during the experiment, and the mass flow, converted by use of approximately constant evaporation energy of approx. 2400 J/g, the most important values of heat flow H_c and moisture flow H_e , each with the unit Watt, are calculated. This means that the result variables

- Moisture Vapor Transmission Rate MVTR [g/h];
- Evaporative Capacity EC [W];
- Storage from the vapor phase ΔW_p [g]

can be determined. Including the measured microclimate parameters temperature, relative humidity or water vapor partial pressure at different spots even the thermodynamic material parameters;

- Thermal resistance R_{ct} [$K \times m^2/W$];
- Water vapor transmission resistance R_{et} [$Pa \times m^2/W$] are calculated.

4. Sensors for Microclimate Measurement

As discussed before the additional demand on reproducible and valuable (substantial) measuring values has to be respected either.

Usually, the measurement of the microclimate is carried out with discrete combi-sensors for temperature and humidity [13]. The inaccuracies that occur in sensor location and occupancy or coverage lead to a scattering of the measured values and limit the quality of the information.

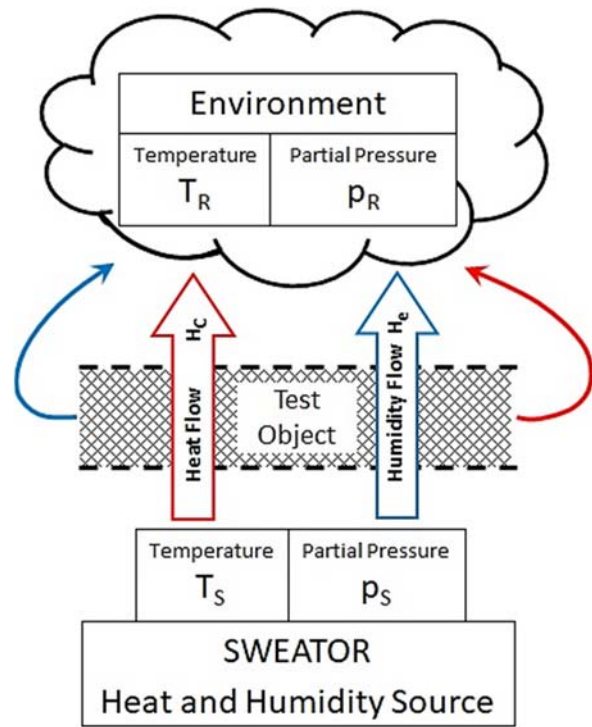


Fig. 6. Heat and moisture transport in SWEATOR simulation.

A solution to avoid the difficulties with single sensors is a defined array of up to 60 sensors combined with an interpolation algorithm calculating the temperature and humidity distribution with all discrete sensor readings. To reduce cable and technical complexity bus-compatible combi-sensors with I2C interface are built into a flexible, thin and compressible spacer mat, which enables two- and even three-dimensional recordings of the microclimates [8].

By laborious market analysis two suitable sensors (Fig. 7) with different specifications and disadvantages have been identified:

- Honeywell HIH8xxx:
 - I2C with up to 128 programmable addresses;
 - $\pm 2\%$ humidity resolution;
 - $\pm 0.5^\circ C$ temperature resolution;
 - Measures: $4 \times 5 \times 2 \text{ mm}^3$;
 - Response time ca. 33 ms;
- Sensirion SHT3x:
 - I2C with 2 selectable addresses;
 - $\pm 1.5\%$ humidity resolution;
 - $\pm 0.1^\circ C$ temperature resolution;
 - Measures: $2.5 \times 2.5 \times 1 \text{ mm}^3$;
 - Response time 4 – 15 ms.

So the Honeywell HIH8xxx can be directly implemented in an array on one bus line, has a sufficient but low resolution in temperature and is bigger than the Sensirion chip. The main disadvantage of the SHT3x is the restricted address range (just 2) for I2C operation with up to 60 sensors on one bus line. To get it also operated an additional PIC is implemented for each SHT3x which serves as a bus respectively address manager.

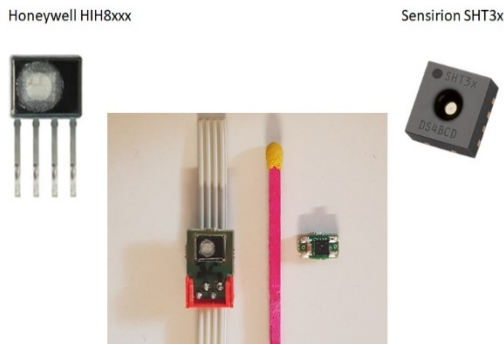


Fig. 7. I2C-sensors processed for measuring microclimate distribution.

This solution offers a so called flash-mode, where converting of all sensors is simultaneously started. The collection of the converted temperature and humidity values is then sequentially. This mode makes sure, that the complete sensor array is read within a few milliseconds, while the reading of 30 Honeywell sensors takes about 1 second.

To connect each sensor unit the SMD sensor chips are mounted on a tiny circuit board (PCB) which allows also the integration of a special crimp connector for the I2C wires and, in case of SHT3x, of the PIC (Fig. 7). Before implementation the programming of different addresses to HIH8xxx as well as address managing routine to PIC of SHT3x is necessary.

By use of a 4 wire ribbon cable the sensor-PCBs can be arranged in any distance or matrix dimensions very quick. To finish the sensor array it will be prefixed on a spacer material and is sewed and covered by a highly breathable mesh material (Fig. 8). The resulting sensor mat is about 4 - 5 mm thick and has for seat or backrest application a typical dimension of $500 \times 500 \text{ mm}^2$. Compared with single sensor measurement the SWEATlog mat takes nearly no influence on the microclimate, is highly flexible and confirms mechanical robustness (connector, cable, sensor-PCB) within many tests.



Fig. 8. SWEATlog logger and sensor array (mat) with up to 60 HIH8xxx sensors at one I2C ribbon (4 wires).

The SWEATlog sensor mats are operated by a logger which works either as stand-alone or USB-controlled. In the USB mode the SWEATlog-app allows an online monitoring and visualisation of the registered values as a heat and humidity map (Fig. 9 and Fig. 10), otherwise these are processed from the data stored on the internal SD-card.

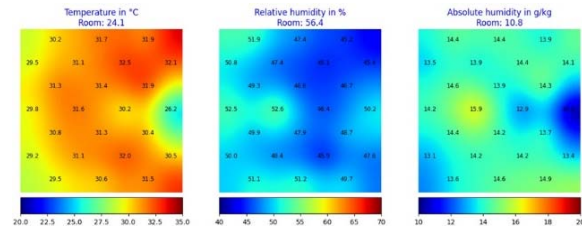


Fig. 9. Heat and humidity map of a proband on the seat of an office chair.

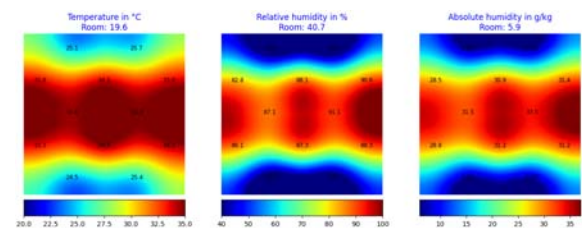


Fig. 10. Heat and humidity map of SWEATOR Torso controlled at 35°C.

The visualizations are calculated by use of each sensor value with a special interpolation algorithm to get the continuous heat and humidity distributions. Additional clustering methods supports the processing of the characteristic values of thermodynamical or physiological relevance [8, 9]. Fig. 9 shows the typical distribution of a proband sitting on a chair showing the contact zones of the buttock and the upper thighs impressively in the heat map, whereas the map of the relative humidity is nearly homogeneous and in the range of the ambient humidity, seeming that the occupant is not sweating. But a look at the absolute humidity map confirms an increase of the humidity in the microclimate as an indicator for additional slight sweating.

To prove the homogeneity of the heat and humidity production of the SWEATOR climate simulation the torso is placed on the sensor mat lying on a seat upholstery. The results displayed in Fig. 10 show quite even distributions of the heat and the humidity in the range of physiological values.

So it can be assumed that the simulated microclimate combined with cluster analysis enable comfort prognosis.

5. Comfort Prognosis

The focus of the SWEATOR simulation combined with SWEATlog sensor mats is primarily set on the

analysis of heat and moisture transport routes and, in particular, on the generation of realistic microclimates for direct comfort assessments. This requires, on the one hand, a secure mapping between regional microclimate conditions (seat, bed, jacket, etc.) and the corresponding comfort sensations of the users, and on the other hand, the appropriate choice of parameters for the simulation system.

For this purpose, a variety of studies on comfort correlations in seating systems, footwear and apparel components could be linked to the comfort areas. After evaluation and harmonization of the rating scales (e.g. [15]), the transition temperature and humidity were determined to reach discomfort in warm temperatures at about 35.5 °C respectively 25 g/kg [7].

The results in Fig. 11 emphasize the correlation between proband and simulation test as well as to the perceptions of the various climate situations (test phase) appearing on car seats with active cooling systems during driving. As expected the humidity perception is weak, but the temperature and comfort perception presents a very good correlation.

This knowledge, in particular the comfort limits can be used to assess various ski boots, tested under 0°C evirons temperature with the SWEATOR foot controlled at 35°C and with adjusted sweat rate to about 15 g per hour and foot. The microclimate has been registered close to the skin (surface of manikin) in the toe area and the medial arch as well as between sock and inside the shoe lining. The results of absolute humidities in Fig. 12 make the comfort prognosis related to the humidity limit of 25 g/kg possible, as just acceptable for the types 2 and 4 and unacceptable for the others.

Consequently any comparison between occupant and simulation results proves the good agreement between the microclimates that occur. Therefore a reliable comfort prognosis based solely on the simulation becomes a practicable and economical option.

6. Conclusions

Following the slogan “what you cannot measure, you can’t improve”, applied on the assessment of climatic product features, requires reproducible and valuable analysis of the microclimate situations between skin and contacting textile, e.g. of apparel.

Although comfort perception shows a high correlation to microclimate’s temperature and humidity the occurring individual diversity of the probands makes the corresponding analysis laborious. To realize precise and economic tests, a heat and moisture source with emission rates adapted to human physiology and the flat or spatial recording of the microclimate in the boundary layers must be available.

Regarding the demands on the microclimate sensor, i.e. precision, placement orientation and at least reproducibility, a special measuring device had to be developed. The SWEATlog system uses combined temperature and humidity sensors with I2C

interface placed in a defined array and fixed in a flexible mat. The visualisation as a heat and humidity map is realized by use of selected algorithms. Interesting thermodynamical as well as comfort related microclimate values are calculated within defined cluster areas.

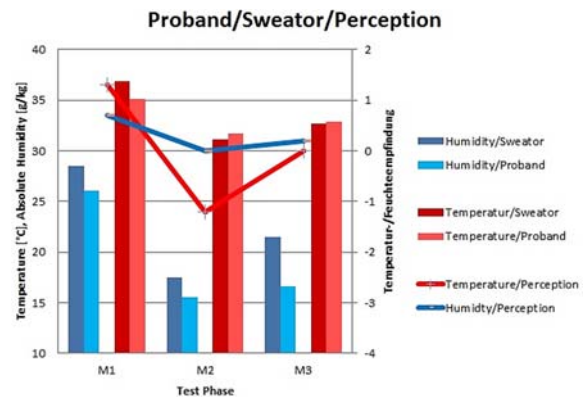


Fig. 11. Comfort correlation of proband and simulation results from seating tests.

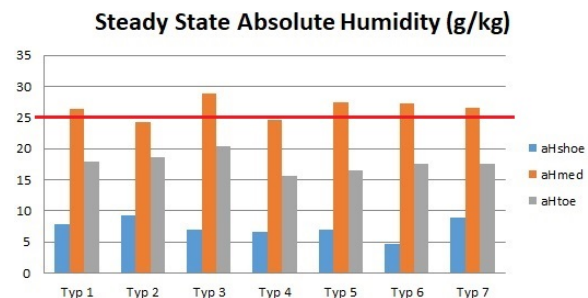


Fig. 12. Comfort prognosis of simulated shoe tests with SWEATOR foot.

The unique combination of SWEATlog sensor mat and the SWEATOR system with anatomically formed and sweating manikins creates the basis for thermophysiological product analyses. Combined with differentiated evaluation methods and with correlations to human comfort perceptions, a reliable comfort prognosis for assessment as well as improvement of clothing or body support products can be achieved.

Future developments should realize an automated clustering of the heat and humidity map by use of AI-technologies (artificial intelligence) to achieve the characteristic evaluation values for climate and comfort management in any microclimate situations.

And, of course, any wireless solution of sensor communication will be preferred to reduce or omit the wiring.

References

- [1]. D. Bektic, Tragekomfortprognose – Korrelationsanalyse ausgewählter Klimasimulationsverfahren, Masterarbeit Hochschule Munich, FK09, 2012.

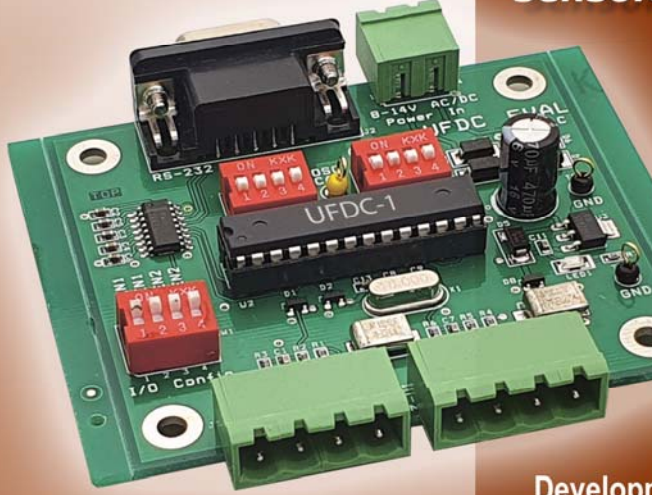
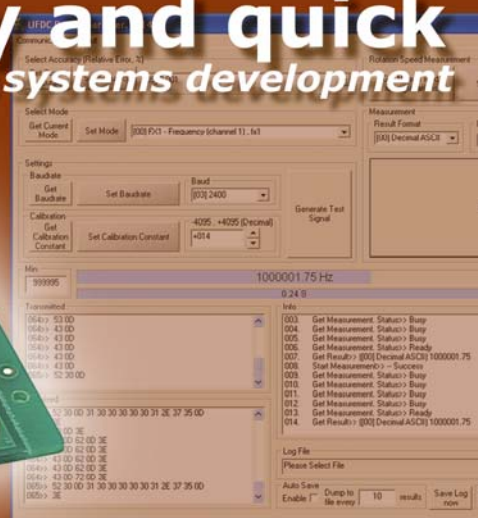
- [2]. E. McCullough, J. Huang, C. S. Kim, An Explanation and Comparison of Sweating Hote Plate Standards, *J. ASTM Int.*, Vol. 1, Issue 7, 2004, pp. 121-133.
- [3]. N. Djongyang, R. Tchinda, D. Njomo, Thermal Comfort – A Review Paper, *Renewable and Sustainable Energy Reviews*, Vol. 14, Issue 9, 2010, pp. 2626-2640.
- [4]. P. O. Fanger, Thermal Comfort, Analysis and Applications in Environmental Engineering, *McGraw-Hill Book Company*, New York, 1973.
- [5]. R. F. Goldman, B. Kampmann, Handbook on Clothing 2nd ed., ICEE (International Conference Environmental Ergonomics), 2007, pp. 2-1 – 2-19.
- [6]. L. Hes, J. Williams, Laboratory Measurement of Thermo-Physiological Comfort; in G. Song (1st ed.), Improving Comfort in Clothing, *Woodhead Publishing Ltd*, Cambridge, 2011, pp. 114-137.
- [7]. B. Kurz, Ch. Russ, Climate Comfort and Product Testing, *Technical Textiles*, 4/5, 2020, pp. 172-174.
- [8]. B. Kurz, Ch. Russ, M. Kurz, Comfort Prognosis by Microclimate Simulation and Measurement, in *Proceedings of the 7th International Conference on Sensors and Electronic Instrumentation Advances (SEIA' 2021)*, Palma de Mallorca, Spain, 2021, pp. 88-89.
- [9]. M. Morena, B. Kurz, R. Krah, How Users perceive the Climate Comfort of Vehicle Seats, *ATZ Worldwide*, Vol. 114, June 2012, pp. 16-20.
- [10]. A. Psikuta, L. C. Wang, R. M. J. Rossi, Prediction of the Physiological Response of Humans Wearing Protective Clothing Using a Themophysiological Human Simulator, *J. Occup. Environ. Hyg.*, Vol. 10, Issue 4, 2013, pp. 222-232.
- [11]. G. Song (ed.), Improving Comfort in Clothing, *Woodhead Publishing Ltd*, Cambridge, 2011.
- [12]. G. Song, S. Mandal, Testing and Evaluating the Thermal Comfort of Clothing Ensembles, in L. Wang (ed.), Performance Testing of Textiles, *Woodhead Publishing of Elsevier*, Cambridge, 2016, pp. 29-64.
- [13]. L. Wang (ed.), Performance Testing of Textiles, *Woodhead Publishing of Elsevier*, Cambridge, 2016.
- [14]. C. Zimmermann, W. Udelhoven, B. Kurz, K.-J. Glitz, Thermal comfort range of a military cold protection glove: database by thermophysiological simulation, *Eur J Appl Physiol*, Vol. 104, 2008, pp. 229-236.
- [15]. ASHRAE: ANSI/ASHRAE, Standard 55 – Thermal Environmental Condition for Human Occupancy, *American Society of Heating, Refrigerating and Air Conditioning Engineers*, Atlanta, 2010.
- [16]. DIN EN ISO 11092:2014-12. Textilien - Physiologische Wirkungen – Messung des Wärme- und Wasserdampfdurchgangswiderstands unter stationären Bedingungen (sweating guarded hotplate test), 2014.



Published by International Frequency Sensor Association (IFSA) Publishing, S. L., 2021 (<http://www.sensorsportal.com>).



Easy and quick sensors systems development

Development Board UFDC-1/UFDC-1M-16

- 16 measuring modes, 2 channels for frequency measurements
- Frequency range from 0.05 Hz up to 7.5 MHz (120 MHz)
- Programmable accuracy from 1 % up to 0.001 %
- RS232 (USB optional)

sales@sensorsportal.com

http://www.sensorsportal.com/HTML/E-SHOP/PRODUCTS_4/Evaluation_board.htm

Deep Learning-Based Detection of Abnormal Respiration Based on Abdominal 3D Shape Dynamically Measured by Moiré Topography

¹Yuki MOCHIZUKI and ^{1,*}Norio TAGAWA

¹ Tokyo Metropolitan University, 6-6 Asahigaoka, Hino, Tokyo, 191-0065, Japan

¹ Tel.: +81-42-585-8416, fax: +81-42-583-5119

* E-mail: tagawa@tmu.ac.jp

Received: 2021 /Accepted: 2021 /Published: 31 October 2021

Abstract: Currently, paramedics cannot make triage judgments in ambulances during emergency transport of infants. If this can be done, it will be possible to select an appropriate destination hospital to provide the most suitable medical care. In this study, we developed a system to detect abnormal respiration by measuring and analyzing three-dimensional abdominal movement using moiré topography and a deep learning model. The performance of the model used in this system was evaluated, and the model was found to be more robust than conventional machine learning models with respect to changes in camera viewpoint.

Keywords: Moiré topography, Active stereo, Deep learning, LSTM, Abdomen shape, Triage, Abnormal respiration.

1. Introduction

Requests for emergency transport of babies and infants are very high, especially at night. In addition, the transportation tends to be concentrated in the major hospitals in the area. Therefore, by appropriately evaluating and diagnosing the condition of them during emergency transportation, they can be transported to a medical institution suitable for their symptoms and provided with necessary medical care. Electronic systems are being developed to continuously monitor the triage vital signs required for them [1]. However, a reliable triage system that can be used adaptively by short-time measurement has not yet been developed. Manual triaging, on the other hand, requires the assessment of respiration, complexion, and consciousness by a skilled healthcare professional. We aim to develop a robust and easy-to-use automatic triage system that can be used in ambulances with poor lighting conditions and high

vibration. As the first step of the research, we investigated a system that measures three-dimensional (3D) movement of the abdomen to detect respiratory abnormalities.

Binocular stereoscopic vision is not sufficient for 3D measurement of the abdomen. That's because the abdomen lacks texture. In recent years, it is conceivable to use an RGB-D camera that has made remarkable progress, but in this study, we use moiré topography. One of the reasons is that in the future, the time variation of the moiré interference fringes before being converted into 3D information may be used for highly sensitive detection of abnormal respiration. In this study, we tried to use a 3D shape reconstructed by moiré topography in order to confirm the intuitive understanding that the time variation of the abdominal shape would be useful for detecting abnormal respiration. In principle, moiré topography cannot determine the absolute 3D shape of an object. To solve this problem and make it easier to measure temporal

changes in abdominal shape, this study proposes a combination of moiré topography and active stereo method.

In this study, a long short-term memory (LSTM) [2] neural network is used to identify abnormal respiration from changes in abdominal 3D shape over time. LSTM models are machine learning models that can make full use of past time series data, which solves the limitation of recurrent neural networks (RNN) that only recent-past data can be used. For the input to the LSTM, the normal vector of the tangent plane at the sampling point on the abdominal surface was used instead of the 3D shape of the abdomen itself. This is because it is taken into consideration that the relative positional relationship between the camera and the target abdomen always fluctuates due to vibration of the environment and changes in the shooting viewpoint during actual use. Through experiments, it was confirmed that the proposed method is more robust to viewpoint changes than the conventional typical machine learning methods.

This paper is an extended version of the proceedings paper [3] at the 7th International Conference on Sensors and Electronic Instrumentation Advances. In particular, the parameter dependence obtained as a result of learning by LSTM is introduced in detail.

2. Measurement System

2.1. Moiré Topography with Active Stereo

In moiré topography, phase values in the range $[0, 2\pi]$ are calculated from moiré interference fringes, and global phase information is restored by unwrapping this local phase information. The depth (distance to the measurement) can be determined by the phase order of each moiré fringe.

The principle of moiré topography (Fig. 1) is that by superimposing a projection of a slit grid pattern on a captured image of the measurement area on which the slit light had been projected, an image with higher order fringes is generated. The lowest order fringe is the moiré fringe.

From the similarity relationship between the triangle ABC and the triangle ASE (Fig. 2), the distance h from the reference grid G to the N^{th} order fringe is calculated by the equation:

$$h_N = \frac{NP_0d}{L - NP_0}, \quad (1)$$

where L is the distance between the light source and the center of the lens, P_0 is the pitch of the reference grid, and d is the projection distance to the reference grid. Since only discrete distances can be measured with Eq. 1, phase information corresponding to the distance between fringes is calculated using a phase-shifting method [4] or the like, such as

$$h(d, \phi, N) = \frac{P_0 d (\phi + 2\pi N)}{2\pi L - P_0 (\phi + 2\pi N)}, \quad (2)$$

where ϕ is the phase between adjacent fringes wrapped from 0 to 2π , and $\phi + 2\pi N$ is the phase measured from the fringes, which is obtained by unwrapping data.

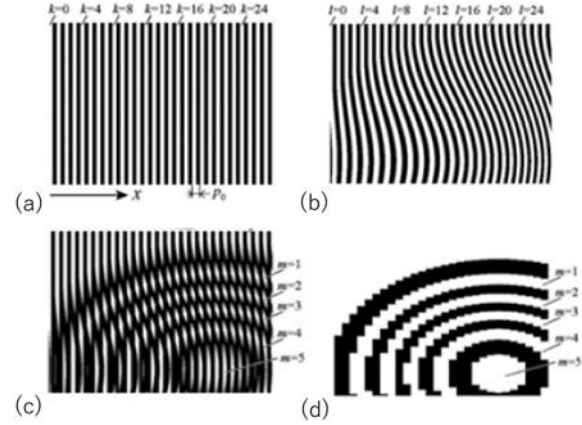


Fig. 1. Generation of moiré interference fringes: (a) projected slit light, (b) captured image with slit light projected onto the target, (c) image with original stripe pattern superimposed on captured image with pattern appearance warped by the targets topography, and (d) extracted moiré interference fringes.

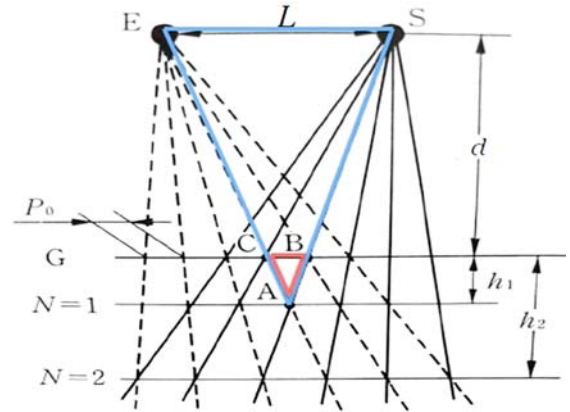


Fig. 2. Principle of distance measurement in moiré topography. S is a point light source, and E is a lens center.

In this study, to obtain local phase information, the sampling moiré method (Fig. 3; [5]) is performed by simple pixel sampling. For each cycle of the captured pattern, N pixels are sampled, and linear interpolation is used to generate N patterns with phase shifts, from which we can calculate the local phase. Fig. 4 shows an example of an abdominal image with captured fringe pattern and the corresponding local phase image. There are several phase unwrapping methods [6-8]. We used the quality map method [6] because of the smooth shape of the abdomen. In this method, reliability of the local phase is calculated (Fig. 5), and the pixels with the highest values are grouped to stack the local phases.

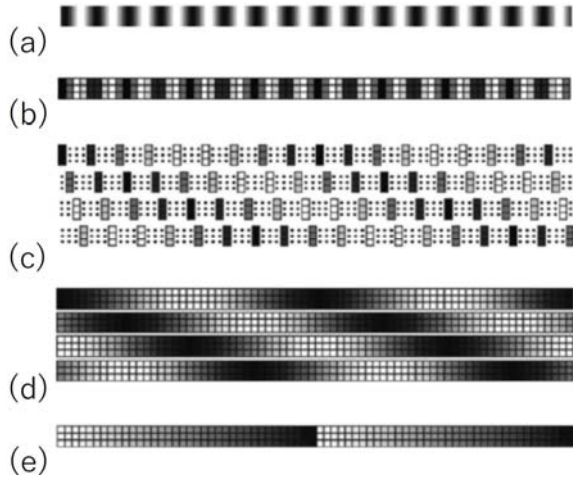


Fig. 3. Phase analysis. (a) original pattern; (b) captured pattern; (c) one cycle of the pattern (N samples); (d) linear interpolation; (e) local phase. (Reprinted from [5]).

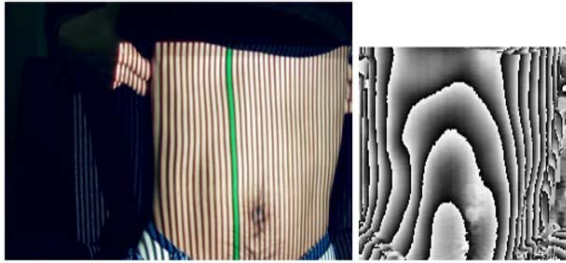


Fig. 4. Captured image (left) and representation of corresponding local phase (right).

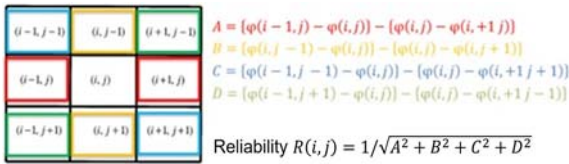


Fig. 5. Reliability definition and the quality map method.

In moiré topography, moiré fringe order cannot be determined, and at least one fringe order, that is, the corresponding distance, must be determined by another method. It is difficult to determine the specific fringe order at each time point because depth measurements, which also change with time, would be necessary. While it is also conceivable to have the patient hold their breath before measurement to determine the order of a particular fringe and then track that fringe in time, this is not realistic. Therefore, we used an active stereo method in which one of the slit lights is colored (green line in Fig. 4), and the depth that colored light is calculated using binocular stereoscopy. This makes it possible to measure depth independently at each time point, which eliminates the need for time-consuming processing. Fig. 6 shows measurement results corresponding to Fig. 4. A measurement error occurs in the slightly shaded area on the right side of the abdominal image in Fig. 4.

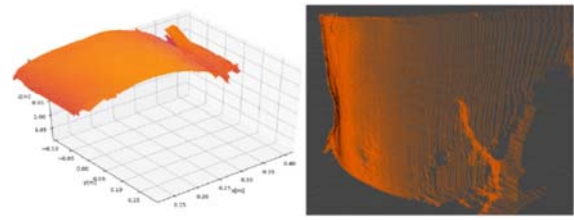


Fig. 6. Resulting 3D measurement of abdominal shape.

However, it is considered that there is no significant effect on the measurement of respiratory status.

A measurement system, with a USB camera and an ultra-small projector controlled by a single-board computer, Raspberry Pi, was manufactured as a prototype (Fig. 7) and used in the experiments described below. The specifications of the camera and the projector used are as follows.



Fig. 7. Moiré measurement system.

Camera

- Model num.: ELP-USBFHD08H-SFV;
- Resolution: 1920 × 1080;
- Sensor: CMOS OV2710;
- Horizontal FOV: 36 deg.

Projector

- Model num.: Ultimems HD301D1;
- Resolution: 1280 × 720, 60 fps;
- Luminous flux: 20 lm ± 10 %;
- Horizontal FOV: 38 deg.

2.2. Detection of Abnormal Respiration

Abnormal respiration such as depressed respiration exhibits different spatial displacements of the abdominal surface than normal respiration—vertical movement of a small area near the epigastrium has an opposite phase to that of the surrounding abdomen during abnormal respiration.

Moiré topography measures the distance from the imaging system to the abdomen. When using this system it is not appropriate to directly use the distance

information for abnormal breathing detection because there are movements of the patient, changes in the imaging viewpoint, and vibrations of the surroundings. The first idea is to convert the distance data into 3D shape data. However, the shape of the abdomen itself is not necessary, and the spatial relationship of temporal unevenness changes is important to monitor the respiratory state. Therefore, in this study, considering the simplification of processing, we decided to calculate and use the unit normal vector on the abdominal surface from the distance data. Namely, time series data consisting of a group of unit normal vectors at multiple points on the abdomen were used as input. Even if the relative positional relationship between the imaging system and the patient's abdomen fluctuates irregularly, the relative relationship of the spatial distribution of the normal vector does not change. Therefore, if such relative relationships are extracted and learned by machine learning without preprocessing such as normalizing the direction of the all normal vectors, less training data is required and an efficient system construction is performed. In the experiments described below, data is collected only when the abdomen and the imaging system are fixed, and machine learning is performed using only that data. Then, the above possibility will be clarified by evaluating the abnormal respiration detection performance in different viewpoints.

Time series data can be handled by normal RNNs. For the periodic data handled in this study, it is important to appropriately extract the necessary information from the past information. Therefore, we use LSTM [2]. An LSTM block (Fig. 8) is used as the intermediate layer of the neural network. The prediction result of the time series is obtained from the previous time series and input, and passed to the next block. Unlike in a normal RNN, in this architecture, a cell state is added to the input element. This cell state stores the LSTM state from the oldest data in the input time series. In the LSTM block, long-term dependence of sequences is learned from the cell state.

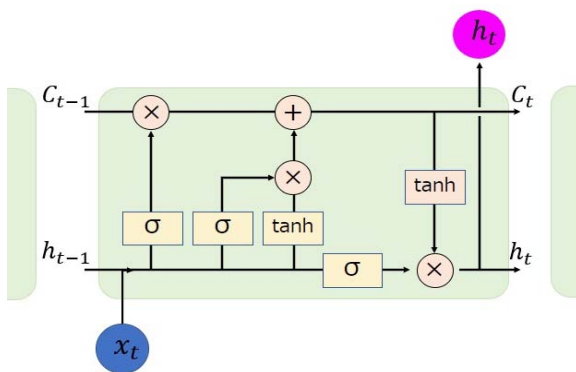


Fig. 8. LSTM block, where h_t is the predicted time series of the input x_t obtained from the prediction result h_{t-1} of the previous time series. A cell state C_{t-1} is added to the input element.

Fig. 9 shows the processing flow of the abnormal respiration detection system. The output in the range $[0, 1]$ corresponds to a probability, where 0 is the probability that respiration is normal and 1 is the probability that respiration is abnormal. The final detection of abnormal respiration will be determined by setting an appropriate threshold for this output. This is beyond the scope of this study and will be the subject of future research. In the experiment, 0.5 was simply set as the threshold.



Fig. 9. Processing flow for abnormal respiration detection based on LSTM.

3. Experiments

3.1. Experimental Conditions

We used normal respiration data to artificially create abnormal respiration data. (Patient participation was not possible as a result of restrictions put in place for the COVID-19 pandemic.) Depressed respiration data were simulated by reversing the vertical movement near the lower part of the sternal pedicle in one cycle of respiration (Fig. 10).

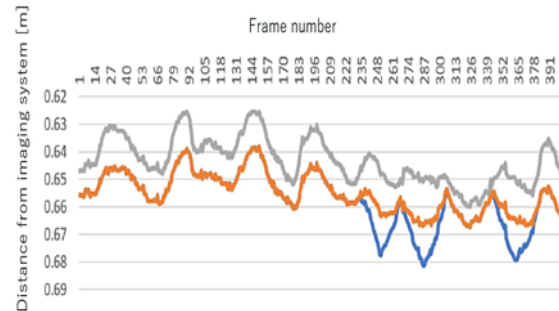


Fig. 10. Time series of distance from the measurement system to abdomen and chest. The gray line is the distance to umbilical region, the orange line is the distance to epigastrium, and the blue is the displacement corresponding to artificially processed depressed respiration.

Examples of 3D abdominal shapes corresponding to normal and depressed respiration are shown in Fig. 11. The vertical movement was in the range (0.5 cm–1.5 cm), and the cycle length was the same as that of the original data.

Measurements were taken from five men (age 20–29 years). For each participant, five measurement sequences of the abdomen and chest were taken, each at a different distance from the camera in 10 cm increments from 50 cm to 90 cm. Each sequence was captured at a rate of 20 frames per second for a duration of 20 seconds. The first

half of the sequence was used as normal respiration; the second half was modified and used as depressed respiration.

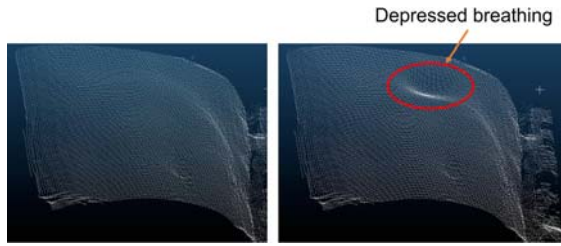


Fig. 11. Examples of abdominal shape for normal (left) respiration and respiratory depression (right). The red ellipse indicates where the phase is opposite to that of the surroundings.

Multiple spatial points on the abdomen, including the epigastrium, were selected by sampling at equal intervals, and the unit normal vector at each sampling point was used as a feature.

Data from four participants (four sequences from each participant's five sequences) were used to train the model, and the remaining sequences (one each from four participants and all five sequences of one person) were used for validation (Table 1). During model training, normal and depressed respiration were input randomly.

Table 1. Details of how to use data for learning and evaluation. A to E indicate the difference between people.

-	50cm	60cm	70cm	80cm	90cm
A	Test	Training	Training	Training	Training
B	Training	Test	Training	Training	Training
C	Training	Training	Test	Training	Training
D	Training	Training	Training	Test	Training
E	Test	Test	Test	Test	Test

The input time series length was 28 frames, the number of sampling points was 32×40 points, the number of hidden layers of LSTM was 384, and the mini batch size was 20 series. The number of pixels constituting the same region (the abdomen extending from the epigastrium to the umbilical region) changed depending on the distance between the measurement system and the target. Since the number of sampling points is predefined, the sampling interval differed for each sequence. Adaptive moment estimation (Adam) was used to optimize learning.

3.2. Experimental Results

First of all, the measurement accuracy of our proposed 3D reconstruction using the manufactured measurement system was evaluated. The measurement accuracy of this system largely depends on the

calibration of the positions and orientations of the projector and camera. After separating the pattern drawn on the calibration jig made of flat plate and the projection pattern generated by the projector, estimate the position and orientation of the projector with respect to the world coordinate system by the method in [9], and then use the method in [10] to estimate the position and the orientation of the camera. Then, they corresponded to each other via the world coordinate system.

In order to confirm the accuracy of the system, the 3D shape of the four-sided pyramid shown in Fig. 12 was measured. The measurement result is shown in Fig. 13.

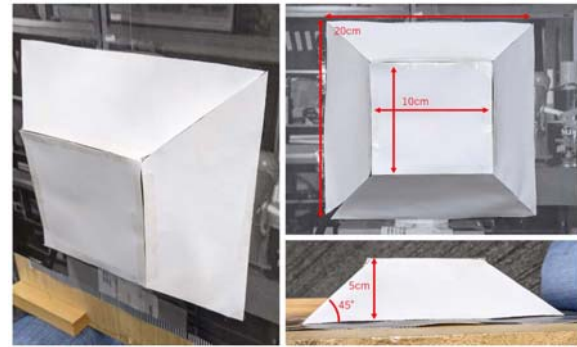


Fig. 12. Measurement target for accuracy verification (four-sided pyramid).

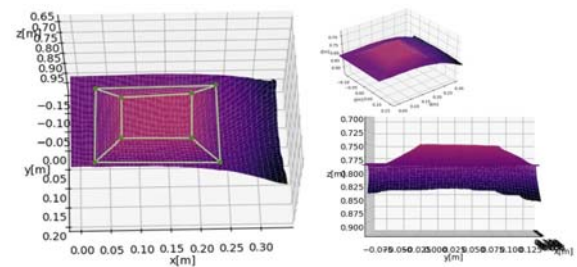


Fig. 13. Measurement result of four-sided pyramid.

From the measurement result, it was found that there was a measurement error of about $+0.5$ cm to $+1.5$ cm in the direction parallel to the depth. It was also found that the error became larger toward the edge. In addition, it was found that there was an error of about -0.95 cm to -0.48 cm in the depth direction. When measuring an object using the active stereo method, which is often used in recent RGB-D cameras, most of the measurement results have an uneven surface, whereas moiré topography using interference fringes obtains a very smooth surface. The above error is larger than the theoretical accuracy of the sampling moiré method. However, due to the characteristics of the proposed method, if an error occurs in the active stereo method, it directly affects the calculation of moiré topography. Since the accuracy of the calibration of the imaging system greatly affects the accuracy of the active stereo

method, it is necessary to confirm the calibration accuracy again. In any case, since the goal of this study is automatic detection of abnormal respiration using time-series data of the abdomen, an error of about 1 cm is sufficiently acceptable.

Next, the experimental results regarding the detection of abnormal respiration will be described. Fig. 14 shows loss convergence during training with the above-mentioned default parameter values. Convergence was fast when the number of layers was large and when the number of sampling points was large; it did not depend on the number of time series.

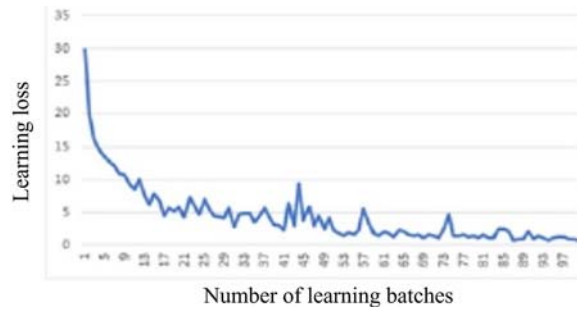


Fig. 14. An example of loss convergence during model training with default parameter values; time series length is 28, the number of sampling points is 32×40 , and the number of hidden layers is 384.

As details, Fig. 15 shows an example of convergence of the loss function during learning when the number of layers is different. As the number of layers increases, the convergence of the loss function becomes slightly faster, but there is a tendency for small increases and decreases. This means that increasing the number of layers, and thus the number of weights in the network, gives the model more freedom to represent and better adapts to the data. According to the discrimination test for the data used for learning, when the number of layers is small, the correct rate with high reliability decreases. However, even if the number of layers is too large, the same correct rate tends to decrease slightly. In this experiment, the correct rate for training data was the highest when the number of layers between 384 and 512. Similarly, we investigated the convergence of the loss function during learning when the number of time series handled by the LSTM was changed. As can be seen from Fig. 16, as the number of time series increases, the overall convergence pattern expands slightly, but there is no significant change. When the number of time series is 20, the loss function fluctuates discontinuously due to the difference in training data. We don't know the exact reason for this, but the time series number 20 may not be appropriate for learning the features common to the data. It was found that the correct rate of normal data decreases when the number of time series is small, although the influence of the number of abnormal data on the correct rate is small. As a result, in this experiment, it was confirmed that

the overall correct rate was high when the number of time series is around 28. Further, Fig. 17 shows the convergence pattern of the loss function when the number of sampling points in the abdomen is increased to 64×80 . It can be seen that the convergence is clearly slower and smoother than that in Fig. 14. The correct rate increased as the number of sampling points increased, but the reliability of discrimination of abnormal respiration decreased significantly. The calculation time is overwhelmingly long when there are many sampling points. Therefore, after that, we set it to 32×40 and conducted an identification experiment on unlearned data.

Performance and processing speed varied depending on the parameters. Since the influence of the time series length was the largest, the results are shown in Table 2 as accuracy. The corresponding inference time is shown in Table 3. The results of the support vector machine (SVM) model, logistic regression (LR), and the hidden Markov model (HMM) are also shown for comparison. The SVM used a second-degree polynomial kernel. LR was optimized using the quasi-Newton method. The HMM was a two-state model. There were no differences in accuracy between LSTM, SVM, and LR models. HMMs, which handle time series information in a manner similar to LSTM models were unexpectedly inaccurate. This may be due to the adoption of a simple two-state model. The longest inference time was for the SVM model, and there was not much difference between LSTM model and LR results. Real-time processing by LSTM is considered possible.

Table 2. Accuracy [%] for different time series lengths. NaN, not a number; LSTM, long short-term memory; support vector machine; LR, logistic regression.

Learning model	Time series length				
	12	20	28	36	NaN
LSTM	91.09	91.76	92.39	92.46	-
SVM	89.26	91.12	92.00	92.46	-
LR	90.45	90.42	91.40	91.91	-
HMM	-	-	-	-	84.41

Table 3. Difference in inference time [seconds] with respect to time series length. LSTM, long short-term memory; CPU, central processing unit; GPU, graphics processing unit; SVM, support vector machine; LR, logistic regression; HMM, hidden Markov model.

Learning model	Time series length				
	12	20	28	36	NaN
LSTM (CPU)	3.1	4.1	6.0	6.7	-
LSTM (GPU)	0.3	0.3	1.4	1.3	-
SVM	428.8	282.2	255.6	238.9	-
LR	1.4	2.2	3.0	4.0	-
HMM	-	-	-	-	30.4

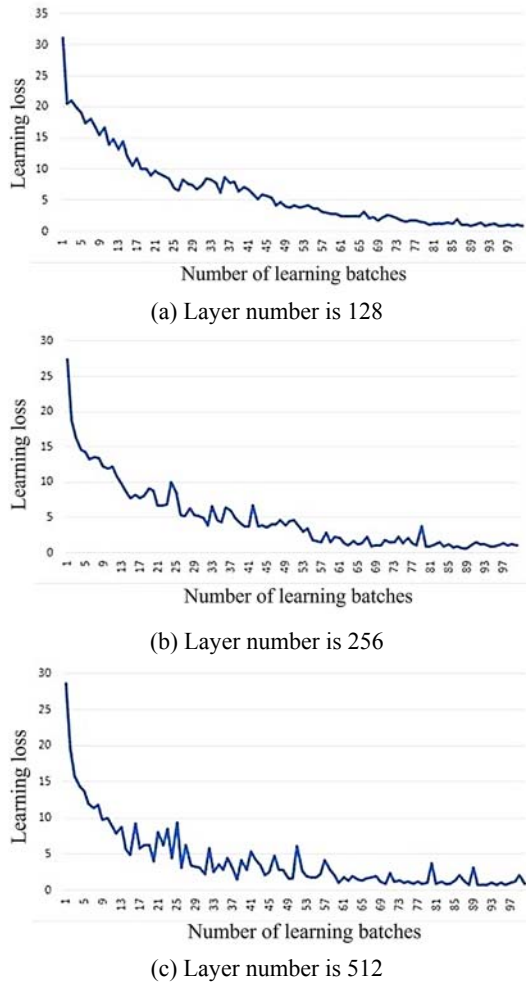


Fig. 15. Changes in convergence of loss function due to the difference in the number of layers.

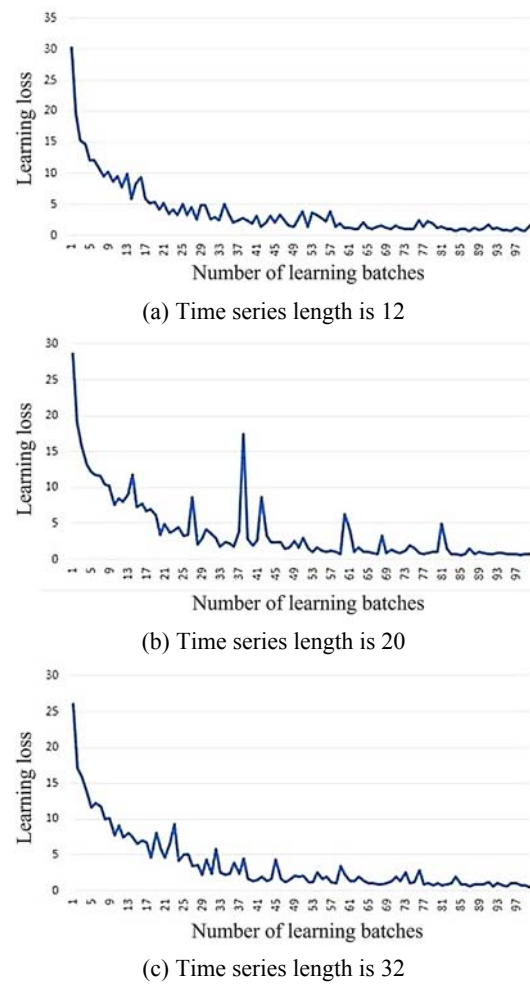


Fig. 16. Changes in convergence of loss function due to difference in the number of layers.

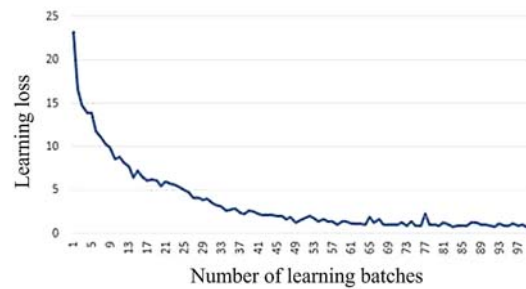


Fig. 17. Convergence of loss function with sampling points of 64×80 .

In actual use, movement of the measurement system and of the patient are expected, and it is difficult to consistently capture images of the abdomen from the front. Therefore, the normal vector calculated when capturing images from the front was rotated to create data corresponding to images captured from an angle. Evaluation data were rotated 30° , -30° , 45° , and -45° around the y-axis to obtain mean accuracy; however, models trained with data measured from the front of the abdomen were used. The LSTM model was able to make robust inferences (Table 4), despite

the change in the camera viewpoint. The HMM was also robust; we consider this to be the effect of the time series information. A strategy for training models using data from multiple directions is also conceivable; this is a topic for the future.

Table 4. Model accuracy. LSTM, long short-term memory; SVM, support vector machine; LR, logistic regression; HMM, hidden Markov model.

LSTM	SVM	LR	HMM
83.15	49.13	47.47	64.55

4. Conclusions

We proposed a method for detecting respiration abnormalities based on 3D measurement of the abdomen using moiré topography and deep learning. The active stereo method was used additionally for moiré topography to determine distance to the reference plane and the relative fringe order. Many other methods for abdominal shape measurement have been proposed [11-15]. Our method of detecting

abnormal respiration is robust to changes in camera viewpoint.

An inexpensive RGB-D camera does not differ much in price from the moiré measurement prototype developed in this study. However, our measurement system can reduce the computational load by using moiré fringes directly to detect abnormal breathing without reconstructing the 3D shape of the abdomen. To this end, it is important to deal with dynamic changes in the relative positional relationship between the imaging system and the abdomen. In addition, dynamic changes in moiré fringes are expected to be more sensitive to abnormal respiratory conditions than changes in the 3D shape of the abdomen. This is an interesting future technical issue.

In this study, the measurement system was used at 20 fps, so the length of the time-series data evaluated for use in LSTM was around 1 second. This time corresponds to about one breathing cycle, as breathing is fast when suffering from an illness. Therefore, in this experiment, abnormal respiration is determined from one respiratory state, and features such as the volatility of the respiratory cycle are not used. In future studies, we will explore the possibility of detecting long-term features of abnormal respiratory conditions, such as changes in respiratory periodicity and the frequency of depressed respiration.

The realization of automated triaging judgments with machine learning is a complex task. For example, triage judgments are also made by integrating other information such as complexion. We used measurement of depressive breathing as the first step in developing an automated triage system.

Acknowledgements

We would like to express our deep gratitude to Dr. Masataka Honda, Professor of Tokyo Metropolitan Children's Medical Center and Dr. Naoki Shimizu, Professor of St. Marianna University School of Medicine, for their suggestions and guidance on this research subject.

References

- [1]. K. Sakanushi, T. Hieda, T. Shiraishi, Y. Ode, Y. Takeuchi, M. Imai, T. Higashino, H. Tanaka, Electronic triage system for continuously monitoring casualties at disaster scenes, *Journal of Ambient Intelligence and Humanized Computing*, Vol. 4, Issue 5, 2013, pp. 547-558.
- [2]. K. Greff, R. K. Srivastava, J. Koutnik, B. R. Steunebrink, J. Schmidhuber, LSTM: a search space odyssey, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 28, Issue 10, 2017, pp. 2222-2232.
- [3]. Y. Mochizuki, N. Tagawa, 3-D measurement of abdomen by moiré analysis and its use for abnormal respiratory conditions by deep learning, in *Proceedings of the 7th Int. Conf. Sensors Engineering and Electronics Instrumentation Advances*, Palma de Mallorca, Spain, 22-24 September 2021, pp. 83-87.
- [4]. L. Jin, Y. Kodera, T. Yoshizawa, Y. Otani, Shadow moiré profilometry using the phase-shifting method, *Optical Engineering*, Vol. 39, Issue 8, 2000, pp. 2119-2123.
- [5]. S. Ri, M. Fujigaki, Y. Morimoto, Sampling moiré method for accurate small deformation distribution measurement, *Experimental Mechanics*, Vol. 50, Issue 4, 2010, pp. 501-508.
- [6]. M. A. Herraiez, D. R. Burton, M. J. Lalor, M. A. Gdeisat, Fast two-dimensional phase unwrapping algorithm based on sorting by reliability following a noncontinuous path, *Applied Optics*, Vol. 41, Issue 35, 2002, pp. 7437-7444.
- [7]. K. Sartor, G. B. Tenali, A. Peter, J. D. V. Allen, M. Rahmes, IFSAR processing using variational calculus, in *Proceedings of the American Society for Photogrammetry and Remote Sensing Annual Conference*, Portland, 28 April-2 May 2008.
- [8]. L. F. Wang, M. Yan, Weighted Kalman filter phase unwrapping algorithm based on the phase derivative variance map, *Applied Mechanics and Materials*, Vol. 475-476, 2014, pp. 991-995.
- [9]. Z. Lei, X. Liu, W. Lu, Z. Lei, L. Chen, L. Zhou, A new calibration method of the projector in structured light measurement technology, *Procedia CIRP*, Vol. 27, 2015, pp. 303-308.
- [10]. Z. Zhang, A flexible new technique for camera calibration, *IEEE Trans. PAMI*, Vol. 22, Issue 11, 2000, pp. 1330-1334.
- [11]. K. Povsic, M. Jezersek, J. Mozina, Real-time 3D visualization of the thoraco-abdominal surface during breathing with body movement and deformation extraction, *Physiological Measurement*, Vol. 36, 2015, pp. 1497-1516.
- [12]. V. D. J. Sam, J. J. J. Dirckx, Real-time structure light profilometry: a review, *Optics and Lasers in Engineering*, Vol. 87, 2016, pp. 18-31.
- [13]. L. Lu, Y. Ding, Y. Luan, Y. Yin, Q. Liu, J. Xi, Automated approach for the surface profile measurement of moving objects based on PSF, *Optics Express*, Vol. 25, Issue 25, 2017, pp. 32120-32131.
- [14]. M. Zhong, X. Su, W. Chen, Z. You, M. Lu, H. Jing, Modulation measuring profilometry with auto-synchronous phase shifting and vertical scanning, *Optics Express*, Vol. 22, Issue 26, 2014, pp. 31620-31634.
- [15]. H. Wu, S. Yu, X. Yu, 3D measurement of human chest and abdomen surface based on 3D Fourier transform and time phase unwrapping, *Sensors*, Vol. 20, Issue 4, 2020, pp. 1091.



Regressing Relative Fine-Grained Change for Sub-Groups in Unreliable Heterogeneous Data Through Deep Multi-Task Metric Learning

* Niall O' Mahony, Sean Campbell, Lenka Krpalkova,
Joseph Walsh and Daniel Riordan

Lero – the Irish Software Research Centre, Department of Agricultural and Manufacturing Engineering; School of Science Technology Engineering and Maths (STEM); Munster Technological University – Kerry Campus, Tralee, Co. Kerry, Ireland
E-mail: niall.omahony@research.ittralee.ie

Received: 15 August 2021 / Accepted: 29 September 2021 / Published: 31 October 2021

Abstract: Fine-Grained Change Detection and Regression Analysis are essential in many applications of Artificial Intelligence. In practice, this task is often challenging owing to the lack of reliable ground truth information and complexity arising from interactions between the many underlying factors affecting a system. Therefore, developing a framework which can represent the relatedness and reliability of multiple sources of information becomes critical. In this paper, we investigate how techniques in multi-task metric learning can be applied for the regression of fine-grained change in real data.

The key idea is that if we incorporate the incremental change in a metric of interest between specific instances of an individual object as one of the tasks in a multi-task metric learning framework, then interpreting that dimension will allow the user to be alerted to fine-grained change invariant to what the overall metric is generalised to be. The techniques investigated are specifically tailored for handling heterogeneous data sources, i.e. the input data for each of the tasks might contain missing values, the scale and resolution of the values is not consistent across tasks and the data contains non-independent and identically distributed (non-IID) instances. We present the results of our initial experimental implementations of this idea and discuss related research in this domain which may offer direction for further research.

Keywords: Multi-task metric learning, Fine-grained change detection, Regression on uncertain data.

1. Introduction

Change Detection (CD), the critically important problem of identifying changes in data, constitutes an extensive body of research as there are many applications requiring efficient, effective algorithms for reliably detecting variation. There are many families of CD algorithms that are suitable for different applications [1]. For example, remote sensing applications and the healthcare industry each

call for different kinds of algorithms depending on the particular use case. Realtime continuous monitoring by wearables may insist on a simple and efficient statistical algorithm that adapts to the data from each user, while more monitoring more complex systems such as the climate or the environment may call for deep learning and hybrid human-machine intelligence in order to capture all sources of variability [2].

This article focuses on CD with respect to regression problems, where the continuous nature of

system scores means they are susceptible to drift and sources of uncertainty due to sensor noise and human error. In these circumstances, the state of the art regression approaches fail to predict subtle deviations for each individual object below the resolution that generalising for the entire population allows. Therefore, instance-based learning approaches are more applicable.

Deep Metric Learning is one such approach where instead of trying to predict a single score/class, the output is mapped to space where you can observe subgroup relatedness. Our has converged towards a Multi-Task Metric Learning (MTML) approach because of the way it learns to map its output to a latent space and how this may be exploited to infer relationships between feature variability and auxiliary background information.

The remainder of this article is organized as follows. In Sect. 2, we briefly introduce notations and algorithms for metric learning. In Sect. 3, we analyse the applicability of metric learning to the problem of fine-grained analysis, in the presence of various sources of uncertainty. In Sect. 4, we review recent advancements in metric learning techniques with respect to each of the challenges presented by our Fine-grained Change Detection application. In Sect. 5, we describe details of some of the techniques we have implemented towards encoding sub-group-specific patterns into latent space with corresponding relative improvements results in regression performance. Lastly, in Sect. 6, we conclude with a brief summary and discussions.

2. Deep Metric Learning

In brief, Deep Metric Learning (DML) approaches learn to represent inputs to a lower-dimensional latent space such that the distance between feature vector representations in this space corresponds with a predefined notion of similarity.

DML methods learn a similarity function, where query and gallery data slices are passed pairwise through a Siamese/Triplet/Quadruplet network. I.e. each set is passed through an identical Neural Network, which output features representative of a query input, often called embeddings. The resulting embeddings are compared using some distance metric (e.g. Euclidean distance) and a loss function (such as triplet-loss) is implemented to minimize the distance between embeddings of the same class (inter-class similarity) and maximize the space between classes (intra-class similarity) so that an accurate prediction can be made through querying which is the nearest embedding to a new embedding [3] as depicted in Fig. 1.

One example of a metric loss function is angular loss. Given a triplet contain an anchor, positive and negative ($\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-$), the angular loss seeks to not only push positive pairs together and negative pairs apart according to distance function δ as triplet loss does, but also constrains the embeddings to a cosine

metric space where the max angle $\angle \mathbf{x}_i^+ \mathbf{x}_i \mathbf{x}_i^-$ denoted as α can be set to make sure negatives are pushed away from the centre of positive clusters (see Fig. 2).

$$[z_i]_+ = [\delta_L^2(\mathbf{x}_i, \mathbf{x}_i^+) - 4 \tan^2 \alpha \delta_L^2(\mathbf{x}_i^-, \mathbf{x}_{i-avg})]_+ \quad (1)$$

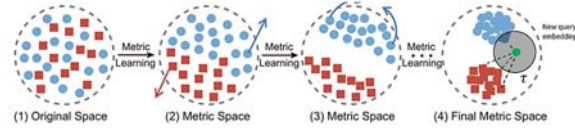


Fig. 1. Metric Learning.

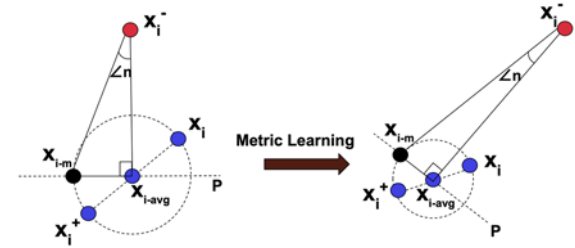


Fig. 2. Angular Loss.

The advantages of DML algorithms include: (1) they are very simple and easy to implement; (2) they are usually efficient in space and time complexity; (3) they are often theoretically guaranteed [4]; (4) they are proven to be robust to adversarial attacks [5]. Furthermore, one of the main drives behind recent research in this area is what can be done when we can learn feature embeddings quantifiable in terms of various meaningful metrics, i.e. various transformations, projections and analyses can be performed on the latent space that take advantage human intuition and knowledge from other domains such as calculus of variation and information geometry.

3. Applications

The research problems considered by this research consist of the simultaneous learning of multiple tasks and doing so with the additional complexities introduced when analysing real data. Examples of such variable features include seasonal and time-of-day variations in outdoor scenes in place recognition tasks for autonomous navigation and age/gender variations in human/animal subjects in classification tasks for medical/ethological studies [5].

Uncertainty in information retrieval can be introduced by noisy observations and the inability to capture the appearance of all objects from every viewpoint. Sources of noise include; e.g., low resolution/faulty sensors and missing/incorrect human-provided training labels. Examples of uncertainty from uncaptured complexity can be found in many applications (in any system which we do not

understand completely in fact). Practical research interests related to modelling uncertainty in complex systems include physics research [6] and robotic perception from limited viewpoints [7].

Adding more labelled data does not eliminate the inherent source of uncertainty. However, modelling uncertainty in training data can improve both the robustness and interpretability of a system [8]. In the remainder of this section, we explore techniques which have been used in conjunction with metric learning to produce accurate predictions even amidst such sources of uncertainty.

3.1. Mitigating Uncertainty Due to Sensor Noise

High precision vision/sensing systems for inspection and categorisation of objects are common in modern industrial settings, but only in regulated and optically controlled environments. One of the primary concerns in such systems is accurate change (point) detection (CD), i.e. the identification of the instant at which the dynamics of the underlying system mechanisms change indicating deviation from normal operating conditions. Fine-grained CD (FGCD) is the process of identifying differences in the state of an object or phenomenon where the differences are class-specific and are difficult to generalise. As a result, many recent technologies which leverage big data and deep learning struggle with this task.

3.2. Mitigating Uncertainty Due to Human Error

Human-provided reference scores entail subjective assessment which is prone to poor inter-observer and intra-observer reliability. This necessitates for the repeatability of estimation to be compared for & between observers [6]. Examples of such scenarios include multi-stage disease diagnosis, student satisfaction questionnaire analysis, customer survey analysis [7]. DML methods have also been devised towards handling missing data using a generative model and semi-supervised learning resulting in a less restrictive scenario than the missing completely at random assumption upon which many existing semi-supervised methods are built [8].

3.3. Mitigating Uncertainty in Robotics

Robotic perception in unregulated environments is an example of the problem of trying to model complexity beyond which can be conceivably captured in a reference dataset. MTML has been shown to be useful for 3D instance segmentation [9], [10] as it can be used to simultaneously group parts of the same object instance, i.e. all points in a point cloud segmented as belonging to a particular instance

of a class, and estimate the direction towards the instance's centre of mass. This makes separating the object instances much simpler and can also provide a metric for the certainty of the instance proposals as the clusters of vectors should all point to a single point and can also be expected to be of a certain size and distance apart.

Obtaining annotations for scores in regression tasks requires certain degree of domain expertise and hence reference information for these scores is only intermittently available. These annotations are also subject to system errors and subjective biases, which often leads to noisy or erroneous labels. Thus, it is essential to be able to learn a metric that could capture the inherent properties of data, without requiring class labels.

4. Related Research

As most CD applications use nominal object classes, many papers applying the latest state-of-the-art to specific application-domains adopt the same methodology, by categorising the output arbitrary classes that ensure even representation across the available dataset. This may come at the cost of not being able to represent the desired output on ordinal, interval or ratio scales which may come naturally in some applications. Thus, they can only measure whether the individual items belong to certain distinct categories and it is not possible to quantify or rank order amongst the categories or perform arithmetic operations. A number of papers have proposed techniques for performing regression with DML [11, 12, 13].

In this section, we review the methods applicable to heterogeneous data from the viewpoint of a number of functionalities, specifically multi-task metric learning, geometry preservation and regression.

4.1. Multi-Task Metric Learning

Multi-Task Metric Learning (MTML) approaches jointly train a DML network to separate w.r.t. multiple tasks, thereby sharing useful information among the tasks, which can significantly improve upon the performance achievable in a single-task setting. MTML has been recently reviewed by [14].

Regarding subgroup and fine-grained analyses, Wang, *et al.* propose a regularized multi-task learning framework with shared representation layers to encode the task relatedness [7]. Similarly, [15] present a framework for detecting the subgroups that have similar characteristics in feature space by using K-means clustering incorporated into the regression stage so that both tasks can be performed simultaneously.

It has been proposed in recent work that multiple features should be used for retrieval tasks to overcome the limitation of a single feature and further improve

the performance. As most conventional distance metric learning methods fail to integrate the complementary information from multiple features to construct the distance metric, a novel multi-feature distance metric learning method for non-rigid 3D shape retrieval which can make full use of the complementary geometric information from multiple shape features has been presented [16]. An alternative formulation for multi-task learning has been proposed by [17] who use a version of the K Nearest Neighbour (KNN) algorithms (large margin nearest neighbour) but instead of relying on separating hyperplanes, its decision function is based on the nearest neighbour rule which inherently extends to many classes and becomes a natural fit for multi-task learning. This approach is advantageous as the feature space generated from Metric Learning crucially determines the performance of the KNN algorithm, i.e. the learned latent space is preserved, KNN just solves the multi-label problem within.

A challenge that has not been well explored in literature is tuple sampling strategies for metric learning in a multi-label setting. A critical element of metric learning is the selection of triplets during training (sometimes referred to as triplet mining). Triplets need to be chosen such that consecutive training batches vary gradually so that the weights learned by the network between batches are actually transferable but also so that all the important variations within the dataset get encountered with enough frequency during training so that the model can capture that variability. Different mechanisms for triplet mining exist. For example, hard triplet mining selects the most difficult triplets for each anchor by calculating the inter-embedding distance between each anchor and all positive and negative embeddings for that anchor. Hard triplet mining selects the most distant embedding in S and the least distant embedding in D for each anchor. Since it is computationally infeasible to aggregate loss over all $O(n^3)$ triplets and hard triplets can cause models to collapse, heuristics are used to speed up convergence. A well known miner is semi-hard negative mining which samples anchors and positives in batches from $\mathcal{X}$ and S , and finds the closest negatives within the batch further away than $D(a, p)$ [18]. Many of these sampling strategies can be quite computationally expensive as they require a forward pass of the network being trained to be run on every image in the dataset. This is why many approaches use mini-batches to fit the computational load within the limits of their machine. Many methods randomly sample a set of images, assuming that a few random parameter vectors will represent certain elementary transformation operations like translation, scaling, rotation, contrast, and colourization.

4.2. Geometry Preserving Metric Learning

The saliency of the embedding space with respect to preserving the local structure of associated

tasks/metrics can be increased by taking measures to preserve the intrinsic geometry of the input space. Many of these approaches utilise information geometry divergence measures such as von Neumann divergence [19] and Wasserstein distance [4].

An alternative type of divergence measure is geometric divergence on graphs and manifolds. This can be achieved by fitting manifolds in latent space and including Riemannian metrics in the loss function [12, 20]. Graph-based methods involve representing feature vectors as graphs to capture interactions (i.e. edges) between individual features (i.e. nodes) and are becoming increasingly popular as there has been a massive surge of interest in geometric deep learning in recent years [21].

In their approach called *Orthogonality based Probabilistic Unsupervised Metric Learning* (OPML), Dutta et al. perform Riemannian Conjugate Gradient Descent (RCGD) to jointly learn the parameters [20]. Their implementation of Riemannian optimisation is stochastic, i.e. it samples the latent space at many randomly chosen points and averages the results to obtain a better approximation. This means that the algorithm can be incorporated with deep neural networks for scaling up, and increasing the computational complexity and also the recognition ability of CNNs of work in this area, which up to quite recently was largely purely academic.

The basis of this field of study is that if latent space embeddings are regularised to lie on a manifold then the inferences made embeddings are regularised to have greater consistency and more rigid inter-variable relationships geometrically. This is made possible because manifold structure allows for a number of operations to be carried out which are advantageous in fine-grained change regression applications. The first is that operations on manifolds can be exploited for regularising the distribution of embeddings such that the model can be taught to have the divergence of embedding clusters be indicative of fine-grained shift in score labels. A Riemannian manifold, or simply a manifold, can be described as a continuous set of points that appears locally Euclidean at every location. This property is often referred to as smoothness. Every smooth manifold has a Riemannian metric. A Riemannian metric (tensor) makes it possible to define several geometric notions on a Riemannian manifold, such as angle at an intersection, length of a curve, area of a surface and higher-dimensional analogues (volume, etc.), extrinsic curvature of sub-manifolds, and intrinsic curvature of the manifold itself.

While the most familiar manifold is Euclidean space, a large number of other, more exotic manifolds can be defined. The manifolds discussed in this paper are examples of matrix manifolds, meaning that they consist of points that can be represented as matrices. More specifically, a manifold is a topological space and a collection of differentiable, one-to-one mappings called charts. At any point on a d dimensional manifold, there is a chart that maps a neighbourhood containing that point to the Euclidean space R^d . This property allows a tangent space to be

defined at every point, which is an Euclidean space consisting of directions that point along the manifold. Tangent spaces are particularly important for optimization because they characterize the set of update directions that can be followed without leaving the manifold [22].

5. Implementation

We implement our experiments on a custom image dataset related to animal health monitoring of 228 animals containing 9 annotations for each image. Some of the annotation labels (3) are up to date at the time of image capture as they are fed from an automated system, while some (2) are provided by human experts on an intermittent basis (every 3 weeks) and missing values were replaced with the closest observation. The remaining 4 values indicate the forward and backward gradient of these expert-provided scores.

The problems to be solved share common challenges around the recognition of subgroup features in dynamic unregulated environments for which include the need to recognise objects never seen before during training, with non-IID instances, in real-time, on limited hardware, in such a way to align dependent information and predict various different types of data.

In working through these problems we have realised a unified metric learning approach which incorporates multi-task and geometry preserving metric learning and have experimented with applying the following components to a deep metric/manifold learning framework [20] trained to perform a multi-label identification task and then being made to infer an auxiliary score and instance-instance change for said score.

The motivation for adopting the methodology of [20] is that enforcing orthogonality between multiple tasks allows natural clusters in the data to be detected, while also simultaneously learning from manual/system annotations where provided. Our application requires that the *intra-class variances* that may occur in our dataset, e.g. due to shift in animal health indication scores whether it be gradual and natural over a period or sudden. Such variances can be captured by adding an orthogonality constraint to the Mahalanobis matrix used for distance estimation. This constraint ensures these relationships are apparent while also allowing the push-pull nature of triplet/angular metric loss function to distribute embeddings that fall between class centres appropriately relying on notions of geometric similarity within the data.

In contrast to Dutta's application, where $\mathcal{X}$ is labelled, we guide our triplet mining strategy on multiple labels. Regarding subgroup and fine-grained analyses, we propose a regularized multi-task learning framework with shared representation layers to encode the task relatedness. A class label matrix was generated to be stored with the image data. The training dataset is randomly sampled for anchors and then iteratively sample for positives and negatives as follows:

Let $\mathbf{x}_i \in \mathbb{R}^d$ be the descriptor of an example i in a dataset $\mathcal{X}$, which is labelled with class label matrix $\mathbf{y}_i$. To form a set of triplets: $\mathcal{T} = \{(\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-)\}_{i=1}^{|\mathcal{T}|}$, each element of which consists of the following:

- 1) $\mathbf{x}_i$, an arbitrary example with $(\mathbf{y}_i)$, which denotes the class label matrix assigned to $\mathbf{x}_i$, $\mathbf{x}_i^+$, another arbitrary example with $(\mathbf{y}_i^+) = (\mathbf{y}_i)$ for at minimum n elements.
- 2) $\mathbf{x}_i^-$, such that $(\mathbf{y}_i^-) = (\mathbf{y}_i)$ for less than n elements. The examples $\mathbf{x}_i$, $\mathbf{x}_i^+$ and $\mathbf{x}_i^-$ are referred to as the *anchor*, *positive* and *negative* respectively.

Jumbo	Lactation	Calving Date	BCS@calving	18/01/2018	02/02/2018	16/02/2018	07/03/2018	22/03/2018	06/04/2018	19/04/2018	04/05/2018	18/05/2018	31/05/2018	19/06/2018
170		320/02/2018	3.25											
172		325/02/2018	3											
325		305/02/2017	4.75	4.5										
360		311/09/2017	3.5	3.5	3.5	3.5								
523		508/09/2017	3.25	4										
570		601/02/2018	3.25	3.25	3	2.75	2.5	2.5	2.75	2.75	2.75	2.75	2.75	2.5
603		415/03/2017												
610		420/09/2017												
790		506/03/2018	3.25	3	3	3	3.25	3.25	3	3	3	3.25	3.25	3.25
796		724/03/2017												

Fig. 3. Our Multi-Task Triplet Mining Strategy: If n of the animal health attribute labels (circled in diagram, details not important) match up for any pair, then they are a positive pair. Note that some values may be missing in the dataset.

For $\mathbf{x}_i \in \mathbb{R}^d$, let $\mathbf{L}^\top \mathbf{x}_i \in \mathbb{R}^l$, denote its learned embedding. Our goal is to learn $\mathbf{L}$ in $\delta_L^2(\mathbf{x}_i, \mathbf{x}_j)$. Let, the learned embeddings of the anchor and the positive be denoted as $\mathbf{L}^\top \mathbf{x}_i$ and $\mathbf{L}^\top \mathbf{x}_i^+$ respectively. The bilinear similarity between them can be expressed as $(\mathbf{L}^\top \mathbf{x}_i)^\top \mathbf{L}^\top \mathbf{x}_i^+ = \mathbf{x}_i^\top \mathbf{L} \mathbf{L}^\top \mathbf{x}_i^+$.

$$\min_{\mathbf{R}, \mathbf{L}} \mathcal{L}(\mathbf{R}, \mathbf{L}) = \sum_{i=1}^{|\mathcal{T}|} (-\log(p_i))$$

Here, $\mathbf{L} \in \mathbb{R}^{d \times l}$ is the parametric matrix of the squared Mahalanobis-like distance metric $\delta_L^2(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i - \mathbf{x}_j)^\top \mathbf{L} \mathbf{L}^\top (\mathbf{x}_i - \mathbf{x}_j)$, for a pair of

examples $\mathbf{x}_i, \mathbf{x}_j \in \mathbb{R}^d$. Ensuring $l < d$ facilitates dimensionality reduction. $\mathbf{R}$ is a parametric matrix that facilitates a weight function based on similarity. $\sum_{i=1}^{|T|} (-\log(p_i))$ is the log likelihood of the triplet set T satisfying the angular constraint. The goal is to learn the parametric matrix $\mathbf{L}$.

Our novel multi-task triplet mining strategy has a number advantages when combined with manifold optimisation techniques. Firstly, because negative pairs can arise from pairs with one or many mismatching variables, if tuned appropriately, the training process may learn to enforce orthogonality of

some of the latent dimensions in correspondence with the difference in the ground truth labels. Secondly, because there is a degree of randomness to the level of mismatch of the input variables, somewhat similar pairs are going to be matched more often than those with few variables matching, hence that similarity is mapped to the latent manifold at a broader scale.

Similarly to [7], we also implement shared representation layers to encode the task relatedness but differ in that we simply calculate the mean squared error (MSE) of a selected dimension of the feature embedding with the label of interest (generalised regression and relative change scores respectively).

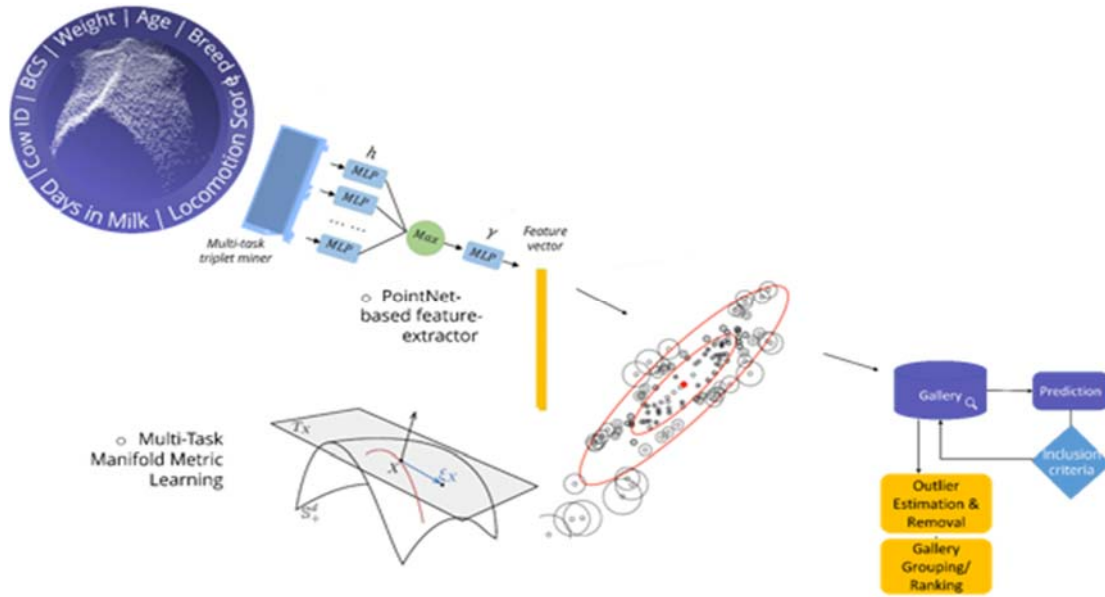


Fig. 4. An overview of our approach, the experiments in this article focus on the middle portion where malanobis distance (shown in red) has a orthogonality preserving constraint [20] which, in coordination with our Multi-Task Triplet Mining Strategy enforces that instances with some deviant variables be orthogonal and hence the deviation is made quantifiable in latent space.

6. Results

We perform experiments to study the following:

- 1) Effect of different sampling settings on the multi-task metric learning results.
- 2) Effect of the different hyperparameters on our method.

In Table 1, we report the results of the multi-task triplet sampler. For our method, we set $\alpha=45^\circ$, and embedding size of 128. We also indicate the nature of an approach, i.e., we use the OPML network.

The test of sensitivity to n , the number of elements in the class label matrix which must match to qualify as a positive sample yielded interesting results. When n is small, the labels which match can vary significantly within and between batches and hence the transition between training iterations is difficult to learn from. This gradually improves as n increases as is reflected in Table 1. Once greater than 6 of the 9 labels in the data needed to match, performance

dropped again, suspect due to the limited number of anchor-positive pairs accepted.

Table 1. Sensitivity of the multi-task triplet sampler and OPML network towards n , the number of elements in the class label matrix which must match to qualify as a positive sample.

n	2	3	4	5	6	7
Network						
OPML	71.2	62.3	50.2	42.5	47.0	61.6

In Table 2, we report the results of α , an important hyperparameter in OPML and the addition of a MSE component to the overall loss function. For our method, we arbitrarily set $n=5$, and embedding size of 128. We also indicate the nature of an approach, i.e., whether it makes use of an additional final layer for classification and regression or not. Note: lower loss is better.

Table 2. Sensitivity towards loss function and α with respect to loss values reached on the test data.

loss \ α	35°	40°	45°	50°	55°	60°
Multi-task/ OPML	73.4	70.5	69.5	68.7	71.7	72.4
Multi-task/ OPML+MSE	241.2	162.3	142.2	152.5	92.0	321.6

These results corresponds with ablation studies by [20] showing the effect of different components of OPML in that a value of α in the mid-range of that tested gave the best results, where α is the upper-bound angle formed by the angle positive-anchor-negative in the angular loss function, however the loss values remained quite high suggesting that the model is not converging well. This may be due to the complexity of the base network compared to that used by [20].

7. Conclusions

The multiple implementation scenarios where MTML solutions have been shown to be useful demonstrate that the proposed method is useful in many AI applications where the algorithm's outputs are to be adapted to each use case.

This paper has also included the results of implementing some of these methods in addition to a novel multi-task triplet sampling strategy to quantify the effect of the hyperparameters of each element. It was found that enforcing too many labels to overlap impeded the convergence of the loss function as there was a limited number of anchor-positive pairs in the dataset. Allowing very little overlap of labels was also detrimental to performance as it allows too much variance between training iterations.

Adding a final layer to regress the embeddings to align to a set of auxiliary outputs hindered the training procedure which may have been due to over-constraining the loss function, to have to learn to space the vectors apart appropriately while simultaneously enforcing a feature which may have no or non-linear correlation to the auxiliary task. To this end, some of the kernel regression techniques [23] may improve performance.

Better results may be achieved if a metric loss function be used in the final layer and the intra-class distances are trained to correspond to the auxiliary tasks using the weighted MSE loss function. The benefit of the interaction of multiple features is to be included in efforts to minimise the regression error as it is why methods which use a Mahalanobis matrix for each metric are so common in MTML solutions.

We intend to further the research in this area by investigating how the mapping element of MTML may be exploited in situations where the salient features vary over time or due to changing underlying variables. One possible avenue would be to develop a technique to calculate the geometric divergence along

each of the dimensions of the latent space/surface w.r.t isolated task-relevant subgroups in order to identify the local covariate geometry with respect to each task and easily recognise subtle changes in the same.

Acknowledgements

This work was supported, in part, by Science Foundation Ireland grant 13/RC/2094 and co-funded under the European Regional Development Fund through the Southern & Eastern Regional Operational Programme to Lero - the Irish Software Research Centre (www.lero.ie). The authors wish to acknowledge the DJEI/DES/SFI/HEA Irish Centre for High-End Computing (ICHEC) for the provision of computational facilities and support.

References

- [1]. W. Shi, M. Zhang, R. Zhang, S. Chen, Z. Zhan, Change detection based on artificial intelligence: State-of-the-art and challenges, *Remote Sensing*, Vol. 12, Issue 10, May 2020, p. 1688.
- [2]. N. O' Mahony, S. Campbell, L. Krpalkova, A. Carvalho, J. Walsh, D. Riordan, Representation learning for fine-grained change detection, *Sensors*, Vol. 21, Issue 13, Jul. 2021.
- [3]. N. O' Mahony, *et al.*, One-shot learning for custom identification tasks; a review, in *Procedia Manufacturing*, Vol. 38, 2019, pp. 186-193.
- [4]. C. Shui, M. Abbasi, L. É. Robitaille, B. Wang, C. Gagné, A principled approach for learning task similarity in multitask learning, in *Proceedings of the IJCAI International Joint Conference on Artificial Intelligence*, Vol. 2019, 2019, pp. 3446-3452.
- [5]. L. Wang, X. Liu, J. Yi, Y. Jiang, C. J. Hsieh, Provably robust metric learning, *Advances in Neural Information Processing Systems*, Vol. 33, 2020, pp. 1-12.
- [6]. Z. Wang, D. M. Anand, J. Moyne, D. M. Tilbury, Improved sensor fault detection, isolation, and mitigation using multiple observers approach, *Systems Science and Control Engineering*, Vol. 5, Issue 1, 2017, pp. 70-96.
- [7]. L. Wang, D. Zhu, Tackling ordinal regression problem for heterogeneous data: sparse and deep multi-task learning approaches, *Data Mining and Knowledge Discovery*, Vol. 35, Issue 3, 2021, pp. 1134-1161.
- [8]. X. Liu, D. Zachariah, J. Wågberg, T. B. Schön, Reliable Semi-Supervised Learning when Labels are Missing at Random, *arXiv*, Issue 2, 2018, pp. 1-8.
- [9]. W. Wang, R. Yu, Q. Huang, U. Neumann, SGPN: Similarity Group Proposal Network for 3D Point Cloud Instance Segmentation, in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2018, pp. 2569-2578.
- [10]. J. Lahoud, B. Ghanem, M. R. Oswald, M. Pollefeys, 3D instance segmentation via multi-task metric learning, in *Proceedings of the IEEE International Conference on Computer Vision*, Vol. 2019-Octob, 2019, pp. 9255-9265.
- [11]. K. Q. Weinberger, G. Tesauro, Metric learning for kernel regression, *Journal of Machine Learning Research*, Vol. 2, Issue May, 2007, pp. 612-619.

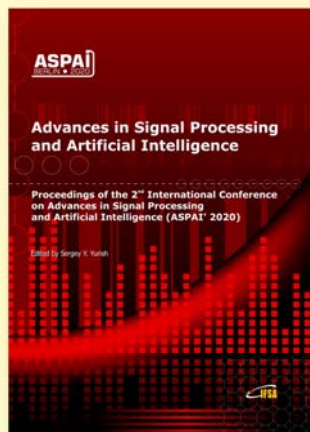
- [12]. R. Huang, S. Sun, Kernel regression with sparse metric learning, *Journal of Intelligent and Fuzzy Systems*, Vol. 24, Issue 4, 2013, pp. 775-787.
- [13]. A. Taha, Y.-T. Chen, T. Misu, A. Shrivastava, L. Davis, Unsupervised Data Uncertainty Learning in Visual Retrieval Systems, *arXiv*, 2019.
- [14]. P. Yang, K. Huang, A. Hussain, A review on multi-task metric learning, *Big Data Analytics*, Vol. 3, Issue 1, Dec. 2018, pp. 1–23.
- [15]. B. Liang, P. Wu, X. Tong, Y. Qiu, Regression and subgroup detection for heterogeneous samples, *Computational Statistics*, Vol. 35, Issue 4, 2020, pp. 1853-1878.
- [16]. H. Wang, H. Li, J. Peng, Xianping Fu, Multi-feature distance metric learning for non-rigid 3D shape retrieval, *Multimedia Tools and Applications*, Vol. 78, Issue 21, Nov. 2019, pp. 30943-30958.
- [17]. K. Q. Weinberger, L. K. Saul, Distance metric learning for large margin nearest neighbor classification, *Journal of Machine Learning Research*, Vol. 10, Jan. 2009, pp. 207-244.
- [18]. R. Manmatha, C. Y. Wu, A. J. Smola, P. Krahenbuhl, Sampling Matters in Deep Embedding Learning, in *Proceedings of the IEEE International Conference on Computer Vision*, Vol. 2017-Octob, 2017, pp. 2859-2867.
- [19]. P. Yang, K. Huang, C. L. Liu, Geometry preserving multi-task metric learning, *Machine Learning*, Vol. 92, Issue 1, Jul. 2013, pp. 133-175.
- [20]. U. K. Dutta, M. Harandi, C. C. Sekhar, Unsupervised Deep Metric Learning via Orthogonality Based Probabilistic Loss, *IEEE Transactions on Artificial Intelligence*, Vol. 1, Issue 1, 2020, pp. 74-84.
- [21]. M. M. Bronstein, J. Bruna, Y. LeCun, A. Szlam, P. Vandergheynst, Geometric Deep Learning: Going beyond Euclidean data, *IEEE Signal Processing Magazine*, Vol. 34, Issue 4, 2017, pp. 18-42.
- [22]. S. Giguere, F. Garcia, S. Mahadevan, A Manifold Approach to Learning Mutually Orthogonal Subspaces, *arXiv*, 2017.
- [23]. K. Q. Weinberger, G. Tesauro, Metric Learning for Kernel Regression, in *Proceedings of the 11th International Conference on Artificial Intelligence and Statistics (AISTATS'2007)*, San Juan, Puerto Rico, March 21-24, 2007, pp. 612-619.



Published by International Frequency Sensor Association (IFSA) Publishing, S. L., 2021 (<http://www.sensorsportal.com>).

Advances in Signal Processing and Artificial Intelligence

Proceedings of the 2nd ASPAI' 2020 Conference



The proceedings contains all accepted and presented papers of both: oral and poster presentations at ASPAI' 2020 conference of authors from 23 countries. The coverage includes artificial neural networks, emerging trends in machine and deep learnings, knowledge-based soft measuring systems, artificial intelligence, signal, video and image processing.

Formats: hardcover (print book) and PDF (e-book), 264 pages
ISBN: 978-84-09-21931-5, e-ISBN: 978-84-09-21930-8
IFSA Publishing, 2020



https://www.sensorsportal.com/HTML/BOOKSTORE/ASPAI_2020_Proceedings.htm

Home Monitoring of Vital Parameters Using Intelligent Sensor and Storage Networks

Ulrich H. P. FISCHER, Jens-Uwe JUST and Fabian THEUERKAUF

Harz University of Applied Sciences, Friedrichstr. 57, 38855 Wernigerode, Germany

Tel.: +49-(0)3943-659351, Fax: +49-(0)3943-659399

E-mail: ufischer@hs-harz.de

Received: 31 July 2021 /Accepted: 30 September 2021 /Published: 31 October 2021

Abstract: The measurement and compilation of vital human data is of particular importance, as it opens up the possibility of supporting a person in their area of life and being able to provide information as to whether diseases are developing or, for example, the gait changes too much so that an early fall could be avoided. Volatile organic components analysis is very interesting possibility for detecting diseases in the home area in a very early stage. Older multimorbid people can also continue to live medically safely in their own home with the help of this supporting analysis of vital parameters and gait parameters, which is the aim of this home monitoring project. Here, the Harz University has developed components for a distributed sensor network for the spectroscopic analysis of air, step analysis and vital parameters collected by a standard smart watch. It measures the number of steps, walking distance, blood pressure, heart rate/ECG and oxygen content of the blood. After analyzing and testing various smart watches, the Fitbit and the OURA ring were used. A test course was developed that lasts around 5 minutes. The sensor system analyses the air in a room by measuring the optical spectral content of VOCs and the gait by a special developed 6D inertial measuring unit (IMU)-sensor in a smart shoe insole. The processing and audio-visual representation of the sensor data fusion represents a probabilistic model as an early warning system for the patient in the home environment. The aim of the work is the dedicated evaluation of the system components of the demonstrator for the subsequent analysis using artificial intelligence for the aggregated client data.

Keywords: Biosensors, Intelligent sensors, Volatile organic components sensors, Sensor fusion of real-time vital data, Gait analysis, Smart shoe sole, Artificial intelligence in medicine.

1. Introduction

Health services, especially for older people, have been introduced very intensively into everyday life in recent years thanks to the rapid development of the transmission technology of the Internet of Things (IoT) [1, 2, 3]. In particular, the focus was on the prevention of diseases and the early detection of disease-related restrictions with a high risk, such as the early detection of a heart attack.

For this purpose, new types of sensor networks [4] came into play, together with intelligent systems for monitoring patients and checking the patient's health

status. The ability of such intelligent systems to save and transmit the recorded vital data is of great importance in many areas of health care in telemedicine. These systems are usually portable (e.g. smart watch) [5, 6], or integrated in the apartment in order to guarantee non-invasive and remote surveillance [7]. Essentially, these systems are used to monitor the symptoms and status of patients for screening, follow-up care, or in the monitoring of care patients [8].

In particular, the area of monitoring in the household for so-called Ambient Assistant Living Systems (AAL) has been pushed very hard in the last

ten years [9]. These systems essentially focus on the physical signals such as heart rate, blood pressure, skin temperature, breathing rate and body movements, as well as step sizes and step frequencies.

The information that is available and collected by these signals can be further processed into clinically relevant information in order to prevent diseases. These wireless sensor networks include a number of biological sensors [7] that can be built and integrated electronically smaller and smaller and can therefore be easily integrated into a smart watch, for example. Each of these sensor systems has specific requirements for recognizing and recording symptoms [10].

In order to be able to provide support to needy and especially elderly people with technical assistance, it is necessary to record both the environmental parameters and the vital parameters of the people. Fig. 1 shows which parameters are typically recorded in the field of medical values: pulse rate, blood pressure, skin temperature, skin resistance, blood oxygen content, movement and steps.

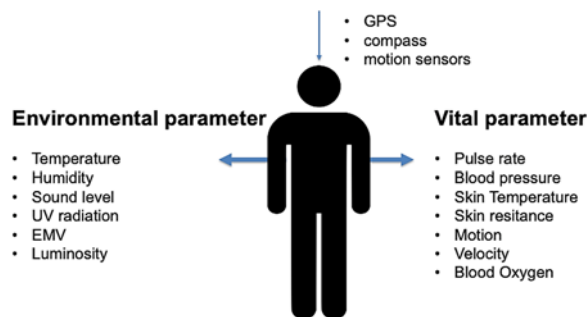


Fig. 1. Important environmental and vital parameters for AAL support of elderly people.

The environment in which the person moves is characterized by temperature, humidity, noise level, light radiation, MV radiation and UV radiation. In addition, the GPS data and the motion sensors with the inertial measuring sensors [11-14] (IMU) can provide further information.

Due to the increased integration capability, the components for applications have become significantly cheaper and are now in the low-cost range. They are relatively easy to install and, thanks to the long battery life, hardly any maintenance is necessary.

In this paper, two new types of sensor systems are presented, which measure the air quality optically in the home, as well as measure the step size, foot pressure and foot temperature at different points on the foot print in an intelligent insole. The collected data are transmitted via radio systems to a data server, from where it is called up and visualized.

Additionally, more vital data are collected by using a standard smart watch (See Chapter 1.3).

The room air sensor uses special absorptions of VOC gases, which indicate the beginning of clinical pictures.

The presence of VOCs (volatile organic compounds) [15, 16] and other substances can provide indications (no conclusive diagnosis) of health problems:

- H_2 (hydrogen) -> lactose intolerance, fructose malabsorption, carbohydrate malabsorption, etc. gastrointestinal diseases;

- C_5H_8 (isoprene) -> indicator for lung cancer (if deficient);

- C_2H_6O (ethanol) -> lack of vitamin E and / or selenium;

- C_3H_6O (acetone) -> insulin deficiency -> poss. Diabetes risk;

- NH_3 (ammonia) -> liver dysfunction (e.g. liver cirrhosis).

In addition to assessing the quality of indoor air for AAL applications, this system is also to be used for the detection of VOC in breathing gas. Since the presence of certain VOCs in exhaled air enables conclusions to be drawn about diseases such as lung cancer or metabolic disorders, the integration of a non-invasive permanent gas analysis in real-time medical care is becoming possible, also in view of increasing bandwidths and decreasing latency times [17].

2. Network Setup

In order to collect and integrate vital parameters and VOC analysis data in a home environment, it is necessary to use an effective and fast network system in combination with an effective database. Such a communication system, which can be reached from every network segment, must be able to post and read structured messages in a data-technically secure manner. Furthermore, it must also guarantee simple client-server administration. These properties are in a so-called "Twitter for computers" (or M2M) with the help of the MQTT protocol guaranteed [18].

As a publisher, a measured value recorder transmits e.g., the step size data to an MQTT server (see Fig. 1), which loads the data as a json object and makes it available to the subscribers as a data source for retrieval. The MQTT server is created locally in the apartment and can be installed on any router so that the data is only saved locally. Special releases can then be given to reading devices such as smartphones or tablets as so-called publishers.

2.1. VOC Sensor

The air sensor is part of a more complex system, the basic mode of operation of which can be seen in Fig. 2. Data recorded by a sensor (e.g., CO_2 concentration) are transferred as (voltage) values to an Arduino board (Particle Photon Development Board module kit), which converts the values into volume concentrations, converts the data generated from it into an MQTT-compliant format and transmits it to a real-time server.

The data is displayed using a special real time Avatar sketch which is presented by Fischer, *et al.* [19]

in more detail. If limits are exceeded, a warning or recommendation is issued (e.g. "Please open window and ventilate" or "Please consult a doctor"). In addition to the data from this sensor, the MQTT server also receives data from different sensors that are developed by second project group.

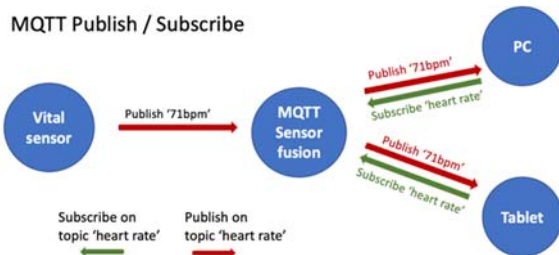


Fig. 2. Vital data fusion by MQTT server.

As can be seen Fig. 3 the processor board is shown, where the on the Arduino processor (1) is located with the corresponding inputs and outputs (2) for the sensors for recording the VOC concentrations. You can also see the power supply (3) and the digital / analog converter (4) and the communication module (5).

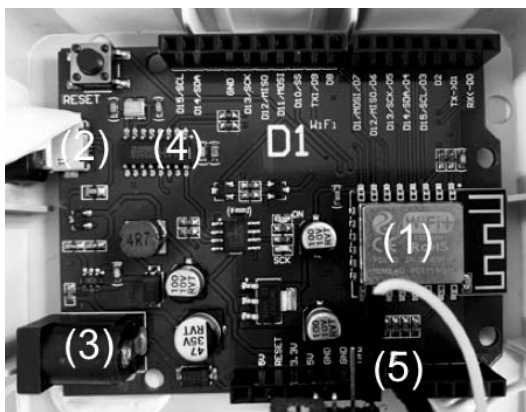


Fig. 3. Arduino setup for VOC analysis and communication module.

2.2. Step Sensor by Smart Shoe Insole

The aim of the second vital sensor project is the development of instruments for the detection of gait changes and for controlled practice in the home environment [20]. The training of coordination skills (right/left coordination) and the feedback on the development of pressure in the lower extremities and the movement pattern (G-sensors) will be carried out in the home environment over a period of 3 months and the influence on the standing and gait safety can be quantified. The sensors are embedded in shoe insoles, which are depicted in Fig. 4. The data provided by the sensors are sent by Bluetooth LE and merged also via the MQTT network and evaluated in a central cloud environment.

The next steps are the evaluation and validation of the analysis data and their fusion with the other recorded vital data for usability in the home environment. It is necessary to carry out the detection of a sufficient number of steps to calculate the parameters. For this purpose, a step course is set up, which can also be carried out in the limited home environment.

2.3. Smart Watch Vital Parameter Acquisition

In addition to the two sensor applications of VOC measurement and the next step with temperature and pressure measurement, a smart watch was used to measure the number of steps, walking distance, blood pressure, heart rate / ECG and oxygen content of the blood. After analyzing and testing various smart watches, the Fitbit Sense [22] and the OURA [23] Ring were used.

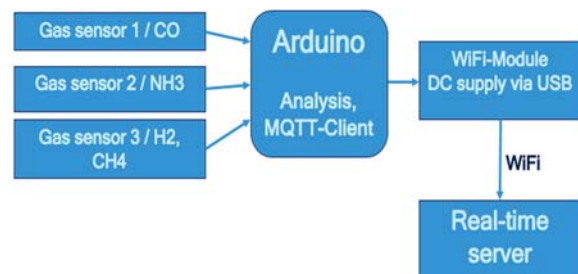


Fig. 4. VOC sensor setup.

A test course was developed that lasts around 5 minutes and includes the following key points:

Starting from 100 steps, either in a corridor in the hallway or as a tour in a room, if the course is to be held in the client's own home. Furthermore, two flights of stairs down and two flights of upstairs will have to be walked up in a stairwell in order to also be able to record changes in heart rate and breathing rate as well as oxygen uptake.

3. Results

3.1. VOC Results

The spectrum of several gases had been recorded using an optical spectrometer (ANDO AQ 8315 with a measuring accuracy of 0.5nm) by the measurement setup depicted in Fig. 4 and Fig. 5. The wavelengths used here correspond to the previously determined absorptions of the relevant substances.

If the substances are present in the air, the light from the source is attenuated in accordance with the concentration, which reduces the voltage values at the sensor output and the volume concentration can be determined. Actually, the temperature sensitivity and needed gas concentration is still causing problems.



Fig. 5. Smart shoe insole with 3D-G sensors, pressure and temperature sensors indicated by green spots (Figure and device fabricated by Thorsis [21]).

As it can be seen in Fig. 6, there are absorption lines of Propane, Butane and Acetylene at several wavelengths in the near infrared appearing.

In Fig. 6 the spectrum is shown between 300 nm in the UV via the visible spectrum up to the infrared region of 1750 nm.

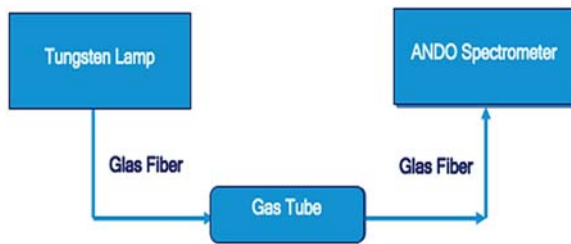


Fig. 6. Measurement setup of optical absorption spectra of VOC absorptions in the near IR region.

The absorption depth of several gases is depicted in logarithmic scale of dBm. Deep absorption lines are depicted in tube 4 boxes:

- Propane (orange) of -7 dB at 1180 nm, 1400 nm (4 dB) and 1710 nm (more than 20 dB);
- Ethine (yellow) absorption is very deep at 1530 nm (25 dB);
- Butane (grey) shows best absorption at 1620 nm with 5 dB and 1700 nm (15 dB);
- A reference measurement (blue line) was performed to show the limit of detection response.

These absorptions are applied in the sensor and must be calibrated to different relative gas pressures according to the VOC grade to the different diseases shown in the introduction of this paper. The calibration is still under work.

A detailed section of the absorption line of acetylene at 1530 nm can be seen in Fig. 8. The output voltage of the electrically amplified signal is shown above the wavelength. One can see, however, that the maximum absorption fluctuates strongly, so that the middle wavelength cannot be clearly identified.

However, the absorption of acetylene is very broad in this area, so that the detection of the VOC acetylene can be easily detected. Both the presence of acetylene

and various concentration levels can be detected. However, an absolute substance concentration is not yet feasible. For this purpose, further detailed investigations must follow.

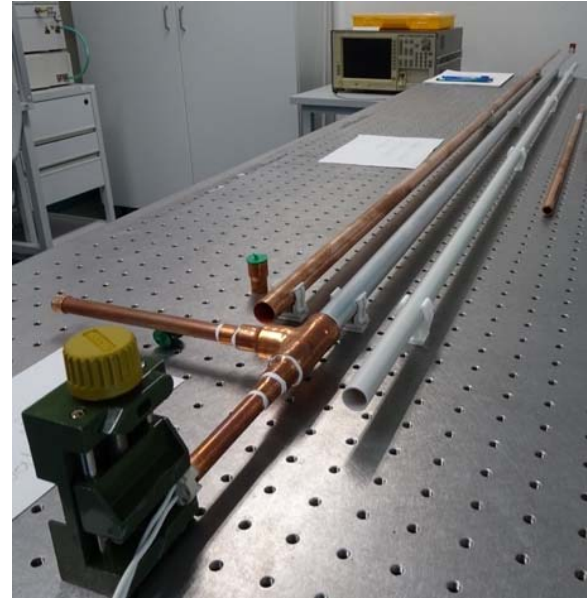


Fig. 7. Photograph of measurement setup.

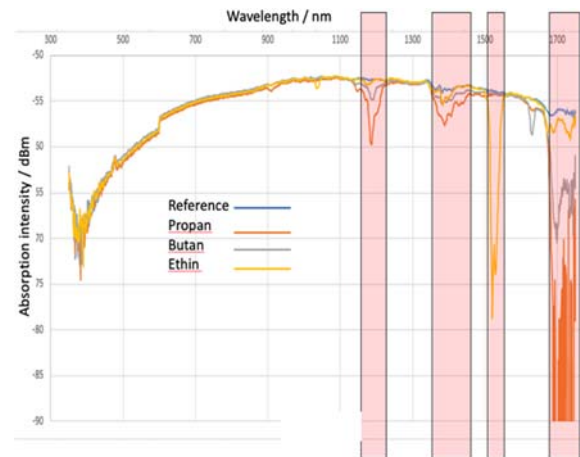


Fig. 8. Optical absorption spectrum of different VOC gas components.

After the clear proof that acetylene can be perfectly detected optically, an alternative modified setup was implemented which uses an LED with the specific wavelength of the absorption of acetylene instead of a broadband light source.

The possibility of using an inexpensive LED, which has a corresponding wavelength of 1530 nm, the absorption of acetylene, seems to be an inexpensive way of realizing an overall system.

The experimental setup was therefore modified and is shown in Fig. 9. The excitation light source (LED) can be seen on the left, which emits exactly into the volume to be measured. Acetylene could now be introduced into the volume of the measuring cell in a

certain concentration and the attenuation of the radiation from the LED at the wavelength of 1530 nm could be observed with a Ge photodetector. The construction is therefore very inexpensive, since an LED with 5-20 € and a photodetector with 5-30 € can be obtained on the market.

The change in the intensity of the LED radiation with the photodetector was recorded with an oscilloscope, as can be seen in Fig. 10. One can clearly see how the voltage signal changes over time and thus the detection of the VOC acetylene can be clearly demonstrated.

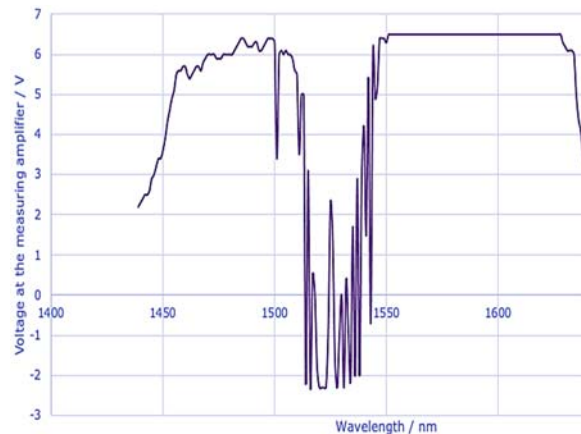


Fig. 9. Absorption line of Acetylene in high wavelength resolution.



Fig. 10. Adapted new setup for absorption measurement of Acetylene.

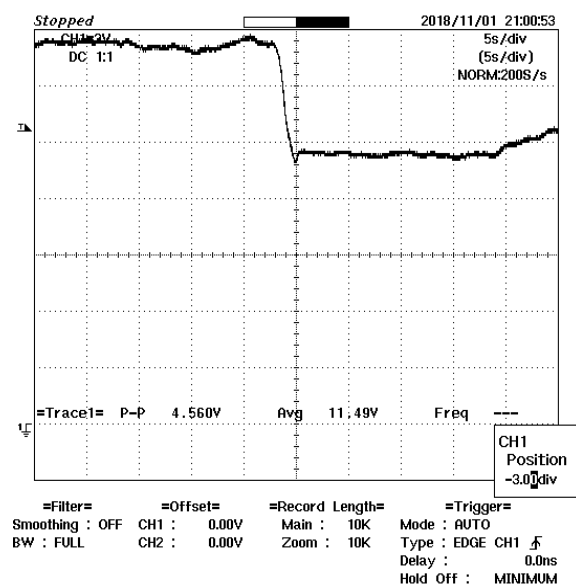


Fig. 11. Signal strength at 1530 nm by excitation with new setup with LED excitation.

The MQTT protocol is used as described above for the transmission of the evaluated VOC concentration values. The syntax is designed as a json object and has the following representation, for example 'HO / Sensor1 / gas1 / concentration'. There is a alerting when limit values are exceeded also with a json object. The patient is then alerted visually and acoustically via the real-time server.

In addition, the following gases are also monitored:

- CO: to increase the safety of air purity in the room
- Ammonia: liver dysfunction
- Ethanol: lack of vitamin E.

3.2. Vital Signs Transmission

In order to transfer the data of the vital parameters of the smart watch and the intelligent shoe sole to the Neuropathy MQTT server, some technical steps are required which should be shown in the following which can be seen in Fig. 12.

The data recorded by the smart watch is transmitted via the so-called Fitbit interface, which is located in the cloud. From there, the data is queried via the neuropathy app and transmitted to the MQTT server, which in turn is available as a data server for the artificial intelligence (AI) tool. Analogously, the data of the intelligent shoe sole is also transferred via the neuropathy app to the MQTT server as a json object and transferred to the database. The artificial intelligence (AI) tool that has yet to be developed will then carry out the evaluation and provide feedback to the client.

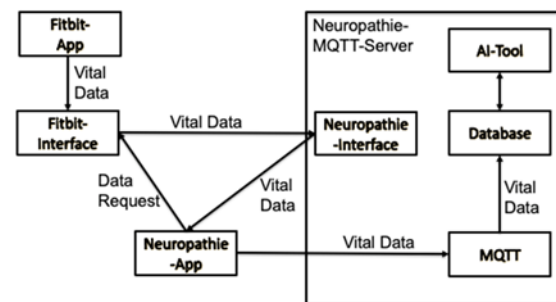


Fig. 12. Data acquisition via smart watch.

Fig. 13 shows the transmission chain of the Json objects in the form of the transmission from the Fitbit app to the MQTT server. The sequence of data shows that the time of data recording and recorded vital values are transmitted according to their arrival and are uniquely stored in the MQTT data. This data can then be called up again from the following database.

After the transfer to the database, the data pool of which can be seen as an excerpt in Fig. 14, the sequence of the json objects and their contents with the corresponding vital data can be recognized.

```
[{"dateTime":"2021-06-02","value":"0"}, {"dateTime":"2021-06-03","value":"0"},
{"dateTime":"2021-06-04","value":"0"}, {"dateTime":"2021-06-05","value":"0"},
{"dateTime":"2021-06-06","value":"0"}, {"dateTime":"2021-06-07","value":"0"},
{"dateTime":"2021-06-08","value":"52"}, {"dateTime":"2021-06-09","value":"175"},
{"dateTime":"2021-06-10","value":"0"}, {"dateTime":"2021-06-11","value":"0"},
{"dateTime":"2021-06-12","value":"0"}, {"dateTime":"2021-06-13","value":"0"},
{"dateTime":"2021-06-14","value":"0"}, {"dateTime":"2021-06-15","value":"0"},
{"dateTime":"2021-06-16","value":"0"}, {"dateTime":"2021-06-17","value":"0"},
{"dateTime":"2021-06-18","value":"0"}, {"dateTime":"2021-06-19","value":"0"},
{"dateTime":"2021-06-20","value":"0"}, {"dateTime":"2021-06-21","value":"0"},
{"dateTime":"2021-06-22","value":"0"}, {"dateTime":"2021-06-23","value":"0"},
```

Fig. 13. Data view as json object for MQTT transfer.

timestamp	user	dateTime	seconds	level
2021-06-30 13:57:07	Cassy	2021-06-28 00:47:30	60	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 00:48:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 00:49:30	240	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 00:53:30	180	restless
2021-06-30 13:57:07	Cassy	2021-06-28 00:56:30	180	awake
2021-06-30 13:57:07	Cassy	2021-06-28 00:59:30	120	restless
2021-06-30 13:57:07	Cassy	2021-06-28 01:01:30	2460	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 01:42:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 01:43:30	120	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 01:45:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 01:46:30	4620	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 03:03:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 03:04:30	1380	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 03:27:30	240	restless
2021-06-30 13:57:07	Cassy	2021-06-28 03:31:30	120	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 03:33:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 03:34:30	2940	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 04:23:30	120	restless
2021-06-30 13:57:07	Cassy	2021-06-28 04:25:30	4020	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 05:32:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 05:33:30	120	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 05:35:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 05:36:30	840	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 05:50:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 05:51:30	300	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 05:56:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 05:57:30	1560	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 06:23:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 06:24:30	60	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 06:25:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 06:26:30	300	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 06:31:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 06:32:30	180	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 06:35:30	60	restless
2021-06-30 13:57:07	Cassy	2021-06-28 06:36:30	60	asleep
2021-06-30 13:57:07	Cassy	2021-06-28 06:37:30	120	restless

Fig. 14. Data view at the data base.

In the further course of the project, the complete data of the VOC sub-project as well as the smartwatch and the intelligent shoe sole will be transferred from the MQTT server to the database and evaluated in cooperation with the medical faculty of the University of Magdeburg. With the help of this evaluation, a subsequent analysis of the aggregated client data should be carried out with the aid of artificial intelligence. The processing and audio-visual representation of the sensor data fusion represents a probabilistic model as an early warning system for the patient in the home environment.

4. Summary

Volatile organic components analysis is very interesting possibility for detecting diseases in the home area in a very early stage. The sub-project VOC acquisition included the development of a distributed sensor system for the spectroscopic analysis of room air as part of the real-time sensor data analysis framework for intelligent assistance systems. It could

be shown that it is possible to detect different gases or gas mixtures with optical technologies. A Demonstrator was realized which detected CO, ammonia, ethanol and ethylene.

Older multimorbid people can also continue to live medically safely in their own home with the help of this supporting analysis of vital parameters and gait parameters, which was the aim of these home monitoring project parts. Here, the Harz University has interconnected components for a distributed sensor network for the spectroscopic analysis of air and step analysis. The sensor system analyses the air in a room by measuring the optical spectral content of VOCs and the gait by special developed 3D G-sensors in a smart shoe insole.

The next steps in the project will be the following: In the first step we need to implement security functions like SSL, AES256 in the transmitted data, because the data are personally and should meet the international security level for secure personal medical data transfer. After that step, we need to integrate an account / profile system that will be able to connect a manifold of clients. These accounts must be integrated into the existing infrastructure of the MQTT data transfer.

After realizing the IT structure, user tests in the lab will be performed as a pretest to finalize the whole system. Afterwards the system will be applied in a 2-month field test in a care station. Here we want to collect real personal data to implement and test the artificial intelligence (AI) tool, which will give the clients clear hints for a safer vital live in their home environment. The AI tool will be developed in cooperation with our medical partner at the Medical Department of the Otto von Guericke University [20].

Acknowledgement

The work was supported by the German Federal Ministry of Education and Research in the program "Zwanzig20 – Partnerschaft für Innovation", contract no. 03ZZ0519I and by Ministry of Science, Economics and Digital of the State of Saxony-Anhalt in the program 'Autonomy in old Age' AiA, contract supported under the EFRE program of the European Union.

References

- [1]. A. P. Matz, J.-A. Fernandez-Prieto, J. Cañada-Bago, U. A. Birkel, A Systematic Analysis of Narrowband IoT Quality of Service., *Sensors*, Vol. 20, Issue 6, 2020, pp. 1636-1642.
- [2]. K. H. Ruhm, Sensor fusion and data fusion – Mapping and reconstruction, *Measurement*, Vol. 40, Issue 2, Feb. 2007, pp. 145-157.
- [3]. J. Li, Q. Ma, A. H. S. Chan, S. S. Man, Health monitoring through wearable technologies for older adults: Smart wearables acceptance model, *Appl. Ergon.*, Vol. 75, 2019, pp. 162–169.

- [4]. N. Mohammadzadeh, M. Gholamzadeh, S. Saeedi, S. Rezayi, The application of wearable smart sensors for monitoring the vital signs of patients in epidemics: a systematic literature review, *J. Ambient Intell. Humaniz. Comput.*, 2020.
- [5]. B. G. Lee, W. Y. Chung, A smartphone-based driver safety monitoring system using data fusion, *Sensors*, Vol. 12, Issue 12, 2012, pp. 17536-17552.
- [6]. S. Majumder, M. J. Deen, Smartphone Sensors for Health Monitoring and Diagnosis, *Sensors*, Vol. 19, Issue 9, 2019.
- [7]. M. J. M. Breteler, E. Al., Wireless Remote Home Monitoring of Vital Signs in Patients Discharged Early After Esophagectomy: Observational Feasibility Study, *JMIR Perioper. Med.*, Vol. 3, Issue 2, 2020.
- [8]. R. Stodczyk, Ambient Assisted Living an Overview of Current Applications, End-Users and Acceptance, *Biomed. J. Sci. Tech. Res.*, Vol. 30, Issue 3, September 2020, pp. 23374-23384.
- [9]. C. Bellos, A. Papadopoulos, R. Rosso, D. I. Fotiadis, Heterogeneous data fusion and intelligent techniques embedded in a mobile application for real-time chronic disease management, in *Proceedings of the IEEE Annual International Conference of the Engineering in Medicine and Biology Society, EMBS*, 2011.
- [10]. U. H. P. Fischer, J.-U. Just, F. Theuerkauf, Intelligent Sensor Network for Home Monitoring of Vital Parameters, in *Proceedings of the 7th International Conference on Sensors Engineering and Electronics Instrumentation Advances (SEIA'2021)*, Palma de Mallorca, Spain, 2021, pp. 103-106.
- [11]. F. Krüger, A. Hein, K. Yordanova, and T. Kirste, "Recognising user actions during cooking task (Cooking task dataset) – IMU Data," *UniRostock Datensever*, p. 4, 2017.
- [12]. K.-C. Broscheid, S. Stoutz, C. Chien-Hsi, L. Schega, The potential of a home-based gait evaluation system with a new low-cost IMU: A pilot study, in *Proceedings of the HEALTH ACROSS LIFESPAN (HAL) International Conference on Healthiness and Fitness Across the Lifespan*, 2018.
- [13]. S. Wlan, Kinect System Interventionsselektion IMUs (on object sensor) Situationsdetektion Datenkonzentration Smartphone (Tablet) Interventionsselektion Datenfusion Situationsdetektion / Datenfusion Arzt / Experte GUI Admin GUI Datenkonzentration Kamerabasierte, p. 11.
- [14]. M. O'Reilly, B. Caulfield, T. Ward, W. Johnston, C. Doherty, Wearable Inertial Sensor Systems for Lower Limb Exercise Detection and Evaluation: A Systematic Review, *Sport. Med.*, Vol. 48, Issue 5, 2018, pp. 1221-1246.
- [15]. P. Pasini, N. Powar, R. Gutierrez-Osuna, S. Daunert, A. Roda, Use of a gas-sensor array for detecting volatile organic compounds (VOC) in chemically induced cells., *Anal. Bioanal. Chem.*, Vol. 378, Issue 1, 2004, pp. 76-83.
- [16]. M. R. R. Khan, B. H. Kang, S. H. Yeom, D. H. Kwon, S. W. Kang, Fiber-optic pulse width modulation sensor for low concentration VOC gas, *Sensors Actuators, B: Chem.*, Vol. 188, 2013, pp. 689-696.
- [17]. U. H. P. Fischer-Hirchert, C. Reinboth, J.-U. Just, Entwicklung von Komponenten für ein verteiltes Sensorsystem zur Echtzeit- Analyse von Atemgas, in *BMC Kongress*, 2019.
- [18]. mqtt.org, MQTT homepage, 2020. [Online]. Available: <https://mqtt.org>.
- [19]. J.-U. Just, C. Reinboth, A. Müller, U. Fischer-Hirchert, Designing a distributed sensor system for the spectral analysis of ambient air, *Biomed. Eng.-Biomed. Tech.*, Vol. 62, Issue s1, 2017, pp. 481-484.
- [20]. P. Mertens, U. H. P. Fischer, Project Neuropathie-iA, <https://forschung-sachsen-anhalt.de/project/autonomie-alter-neuropath-23428>, 2021. [Online]. Available: <https://forschung-sachsen-anhalt.de/project/autonomie-alter-neuropath-23428>.
- [21]. THORSYS Shoe Sole, 2021.
- [22]. FITBIT SENSE, 2021.
- [23]. OURA Ring Website, 2021. [Online]. Available: https://ouraring.com/?utm_campaign=G_SEM_Brand_Intent_ROW&g_network=g&g_adid=479281245047&g_keyword=oura-ring&g_adtype=search&g_adgroupid=112468462265&g_keywordid=kwd-305035554360&g_acctid=553-919-5922&g_campaign=G_SEM_Brand_Intent_ROW&g_campaignid=11599005276&utm_medium=cpc&utm_source=google&gclid=CjwKCAjwq9mLBhB2EiwAuYdMtSortkPf2ocbjjk7Awwvlrz_Mw1XGKQJefCO53uMPtXLjojR6X59RoC6LIQAvD_BwE



Turbo Coded Single User Massive MIMO

¹ K. Vasudevan, ¹ A. Phani Kumar Reddy, ¹ Gyanesh Kumar Pathak
and ² Mahmoud Albreem

¹ Department of Electrical Engineering, Indian Institute of Technology Kanpur-208016, India

² Department of Electrical Engineering, University of Sharjah, Sharjah 27272, UAE

E-mail: vasu@iitk.ac.in, phani@iitk.ac.in, pathak@iitk.ac.in, mahmoud.albreem@asu.edu.om

Received: 2 July 2021 /Accepted: 6 September 2021 /Published: 31 October 2021

Summary: This work deals with turbo coded single user massive multiple input multiple output (SU-MMIMO) systems, with and without precoding. SU-MMIMO has a much higher spectral efficiency compared to multi-user massive MIMO (MUMMIMO) since independent signals are transmitted from each of the antenna elements (spatial multiplexing). MU-MMIMO that uses beamforming has a much lower spectral efficiency, since the same signal (with a delay) is transmitted from each of the antenna elements. In this work, expressions for the upper bound on the average signal-to-noise ratio (SNR) per bit and spectral efficiency are derived for SU-MMIMO with and without precoding. We propose a performance index.

$f(N_t)$, which is a function of the number of transmit antennas N_t . Here $f(N_t)$, is the sum of the upper bound on the average SNR per bit and the spectral efficiency. We demonstrate that when the total number of antennas (N_{tot}) in the transmitter and receiver is fixed, there exists a minimum value of $f(N_t)$, which has to be avoided. Computer simulations show that the bit-error-rate (BER) is nearly insensitive to a wide range of the number of transmit antennas and re-transmissions, when N_{tot} is large and kept constant. Thus, the spectral efficiency can be made as large as possible, for a given BER and N_{tot} .

Keywords: Flat fading, Precoding, Re-transmissions, Single user massive MIMO, Spectral efficiency, Turbo codes.

1. Introduction

Wireless telecommunication standards for 6G and beyond, aim for peak data rates per user of the order of 100 gigabits per second (Gbps). This can only be achieved using antenna arrays having a large number of antenna elements at both the transmitter and receiver (single user massive multiple input multiple output (SU-MMIMO)) and carrier frequencies of the order of terahertz (mmwave frequencies). Much of the existing literature on massive MIMO deals with multi user case (MU-MMIMO) [1–18], where the base station is equipped with a large number of antennas and each

user has only a single antenna. SUMMIMO has not yet been studied, excepting for a few works with equal number of transmit and receive antennas and ideal receiver [19,20], orthogonal frequency division multiplexing (OFDM)-based practical receiver which estimates timing, carrier frequency offset and channel impulse response [21,22], analysis of probability of erasure (probability of not detecting an OFDM frame when it is present) [23, 24], ideal receiver with unequal number of transmit and receive antennas with precoding [25,26]. SU-MMIMO is also presented in [27, 28]. SU- and MU-MIMO for distributed antenna systems (antennas that are spatially far apart) is studied

in [29], which is quite different from what is presented in this work (for example see Fig. 2 of [21]).

Let us look at the differences between SU- and MU-MMIMO [27, 28]:

1. In MU-MMIMO, beamforming is possible only in the downlink, whereas in SU-MMIMO, beamforming is possible in both uplink and downlink.
2. Spatial multiplexing is not possible in MU-MMIMO since the user (mobile handset) has only one antenna, whereas in SU-MMIMO spatial multiplexing is possible in both uplink and downlink.

The difference between beamforming and spatial multiplexing is enumerated below [27, 28]:

1. Beamforming has a lower spectral efficiency, since the same signal (with a delay) is transmitted from a large number of antenna elements. Spatial multiplexing has a higher spectral efficiency, since independent signals are transmitted from a large number of antenna elements.
2. Beamforming yields a highly directive pencil beam. Spatial multiplexing requires a rich scattering channel for effective operation and has no directivity.

This work describes two methods of implementing SU-MMIMO with unequal number of transmit and receive antennas, namely:

1. With precoding [25, 26].
2. Without precoding.

SU-MMIMO without precoding and equal number of transmit and receive antennas has been described earlier in [19, 20]. We now briefly discuss the topic of precoding.

Precoding at the transmitter is a technique that dates back to the era of voiceband modems or wired communications [30–36]. The term “precoding” is quite generic and refers to one or more of the many different functionalities, as given below:

1. It compensates for the distortion introduced by the channel. Note that channel compensation at the receiver is referred to as equalization [37–43]. Here, channel compensation implies removal or minimization of intersymbol interference (ISI).
2. It performs error control coding, besides channel compensation.
3. It shapes the spectrum of the transmitted signal, and renders it suitable for propagation over the physical channel. Note that most channels do not propagate a dc signal and precoding is used to remove the dc component in the message signal. At this point, it is important to distinguish between a message signal and the transmitted signal.

In the context of wireless multiple input, multiple output (MIMO) systems, the main task of the precoder is to remove interchannel interference (ICI), either for single-user or multi-user case [44–50]. It should be observed that precoding requires knowledge of the channel state information (CSI) at the transmitter,

which is usually fed back by the receiver to the transmitter. The receiver estimates CSI from a known training signal that is sent by the transmitter. CSI usually refers to the channel impulse response (CIR) or its statistics (mean and covariance), depending on the type of precoder used. Thus, precoding requires the channel to be time invariant or wide sense stationary (WSS) over at least one transmit and receive duration. Moreover, precoding can only be performed on systems employing time division duplex (TDD), which is a method of half duplex telecommunication. In other words, the channel needs to be reciprocal, that is, the CIR from the transmitter to receiver must be identical to that from receiver to transmitter.

In this work, we describe an elegant precoding method which reduces ICI in single user massive MIMO systems and compare it with the case without precoding [19, 21]. Rayleigh flat fading channel is assumed. If the channel is frequency selective, orthogonal frequency division multiplexing (OFDM) can be used e.g. single input single output (SISO) OFDM [43,51,52], single input multiple output OFDM [53] or MIMO OFDM [21, 22, 54, 55].

This work is organized as follows. Section 2 describes the signal model with and without precoding. In Section 3 precoding for SU-MMIMO is discussed. The case without precoding is presented in Section 4. Section 5 presents the simulation results and Section 6 gives the conclusions.

2. Signal Model

Consider a precoded MIMO system with N_t transmit and N_r receive antennas, as shown in Fig. 1 [25]. The precoded received signal in the k^{th} ($0 \leq k \leq N_{rt} - 1$, k is an integer), re-transmission is given by

$$\tilde{\mathbf{R}}_k = \tilde{\mathbf{H}}_k \tilde{\mathbf{H}}_k^H \mathbf{S}^p + \tilde{\mathbf{W}}_k, \quad (1)$$

where $\tilde{\mathbf{R}}_k \in \mathbb{C}^{N_r \times 1}$ is the received vector, $\tilde{\mathbf{H}}_k \in \mathbb{C}^{N_r \times N_t}$ is the channel matrix and $\tilde{\mathbf{W}}_k \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian noise (AWGN) vector. The transmitted symbol vector is $\mathbf{S}^p \in \mathbb{C}^{N_t \times 1}$, whose elements are drawn from an M -ary constellation. Boldface letters denote vectors or matrices. Complex quantities are denoted by a tilde. However tilde is not used for complex symbols $\mathbf{S}^p$. The elements of $\tilde{\mathbf{H}}_k$ are statistically independent, zero mean, circularly symmetric complex Gaussian with variance per dimension equal to σ_H^2 , as given by (2) of [19]. Similarly, the elements of $\tilde{\mathbf{W}}_k$ are statistically independent, zero mean, circularly symmetric complex Gaussian with variance per dimension equal to σ_W^2 , as given by (3) of [19].

The system model without precoding is shown in Fig. 2 which is similar to Figure 1 of [19], accepting that here the number of transmit antennas is not equal to the number of receive antennas. The received signal without precoding, in the k^{th} re-transmission is given by (see also (1) of [19])

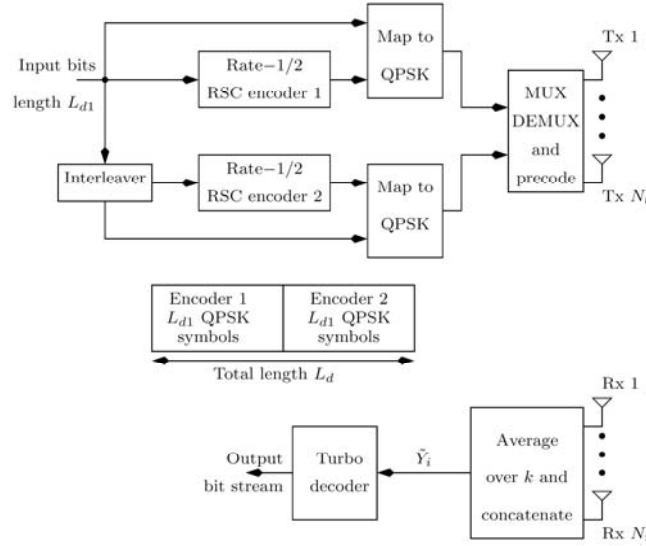


Fig. 1. System model with precoding.

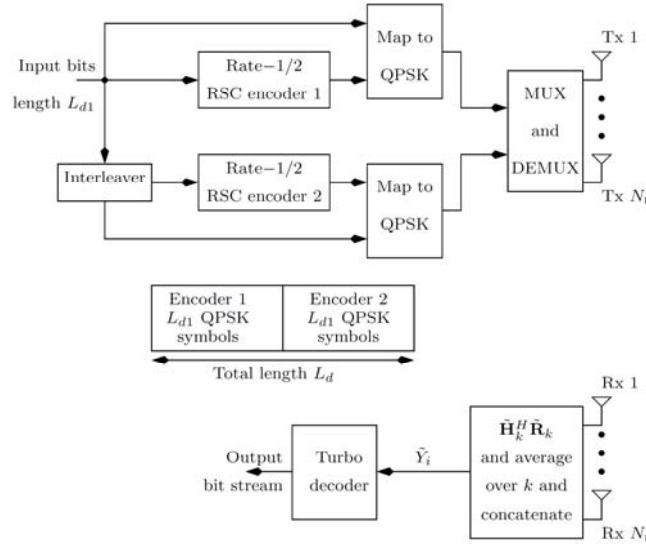


Fig. 2. System model without precoding.

$$\tilde{\mathbf{R}}_k = \tilde{\mathbf{H}}_k \mathbf{S} + \tilde{\mathbf{W}}_k \quad (2)$$

where $\mathbf{S} \in \mathbb{C}^{N_t \times 1}$ whose elements are drawn from an M -ary constellation. In this work, the elements of $\mathbf{S}^p$ and $\mathbf{S}$ are turbo coded and mapped to a QPSK constellation with coordinates $\pm 1 \pm j$, as depicted in Fig. 1. Moreover, here $\tilde{\mathbf{H}}_k$ is an $N_r \times N_t$ matrix, whereas in [19] $\tilde{\mathbf{H}}_k$ is an $N \times N$ matrix. We assume that $\tilde{\mathbf{H}}_k$ and $\tilde{\mathbf{W}}_k$ are independent across re-transmissions, hence (4) in [19] is valid with N replaced by N_r . We now proceed to analyze the signal models in (1) and (2).

3. Precoding

The i^{th} element of $\tilde{\mathbf{R}}_k$ in (1) is

$$\tilde{R}_{k,i} = \tilde{F}_{k,i,i} S_i + \tilde{I}_{k,i} + \tilde{W}_{k,i} \quad \text{for } 1 \leq i \leq N_r \quad (3)$$

where

$$\begin{aligned} \tilde{F}_{k,i,i} &= \sum_{j=1}^{N_t} |\tilde{H}_{k,i,j}|^2 \\ \tilde{I}_{k,i} &= \sum_{\substack{j=1 \\ j \neq i}}^{N_r} \tilde{F}_{k,i,j} S_j \\ \tilde{F}_{k,i,j} &= \sum_{l=1}^{N_t} \tilde{H}_{k,i,l} \tilde{H}_{k,j,l}^* \quad \text{for } i \neq j. \end{aligned} \quad (4)$$

The desired signal in (3) is $\tilde{F}_{k,i,i} S_i$, the interference term is $\tilde{I}_{k,i}$ and the noise term is $\tilde{W}_{k,i}$. Now

$$\begin{aligned}
E[\tilde{F}_{k,i,i}^2] &= E\left[\sum_{j=1}^{N_t} |\tilde{H}_{k,i,j}|^2 \sum_{l=1}^{N_t} |\tilde{H}_{k,i,l}|^2\right] \\
&= E\left[\sum_{j=1}^{N_t} \tilde{H}_{k,i,j,I}^2 + \tilde{H}_{k,i,j,Q}^2\right. \\
&\quad \left.\times \sum_{l=1}^{N_t} \tilde{H}_{k,i,l,I}^2 + \tilde{H}_{k,i,l,Q}^2\right] \\
&= 4\sigma_H^4 N_t (N_t + 1)
\end{aligned} \quad (5)$$

where the subscript “I” denotes the in-phase part and the subscript “Q” denotes the quadrature part of a complex quantity and the following relation has been used [56, 57]

$$E[X^4] = 3\sigma_X^4, \quad (6)$$

where X is a zero-mean, real-valued Gaussian random variable with variance σ_X^2 . Moreover from (4) and (2) in [19]

$$E[\tilde{F}_{k,i,i}] = 2\sigma_H^2 N_t. \quad (7)$$

We also have

$$\begin{aligned}
E[|\tilde{I}_{k,i}|^2] &= E\left[\sum_{j=1}^{N_r} \tilde{F}_{k,i,j} S_j\right. \\
&\quad \left.\times \sum_{l=1}^{N_r} \tilde{F}_{k,i,l}^* S_l^*\right] \\
&= \sum_{j=1}^{N_r} \sum_{l=1}^{N_r} P_{av} E[\tilde{F}_{k,i,j} \tilde{F}_{k,i,l}^*] \delta_K(j-l) \\
&= P_{av} \sum_{j=1}^{N_r} E[|\tilde{F}_{k,i,j}|^2]
\end{aligned} \quad (8)$$

where $\delta_K(\cdot)$ is the Kronecker delta function [19, 43], we have assumed independence between $\tilde{F}_{k,i,j}$ and S_j and [19]

$$\begin{aligned}
E[S_j S_l^*] &= P_{av} \delta_K(j-l) \\
&= 2\delta_K(j-l).
\end{aligned} \quad (9)$$

Now

$$\begin{aligned}
E[|\tilde{F}_{k,i,j}|^2] &= E\left[\sum_{l=1}^{N_t} \tilde{H}_{k,i,l} \tilde{H}_{k,j,l}^*\right. \\
&\quad \left.\times \sum_{m=1}^{N_t} \tilde{H}_{k,i,m}^* \tilde{H}_{k,j,m}\right] \\
&= \sum_{l=1}^{N_t} \sum_{m=1}^{N_t} E[\tilde{H}_{k,i,l} \tilde{H}_{k,i,m}^*] \\
&\quad \times E[\tilde{H}_{k,j,m} \tilde{H}_{k,j,l}^*] \\
&= \sum_{l=1}^{N_t} \sum_{m=1}^{N_t} 4\sigma_H^4 \delta_K(l-m) \\
&= 4\sigma_H^4 N_t.
\end{aligned} \quad (10)$$

Substituting (10) in (8) and using (9) we get

$$E[|\tilde{I}_{k,i}|^2] = 8\sigma_H^4 N_t (N_r - 1). \quad (11)$$

Due to independence between $\tilde{I}_{k,i}$ and $\tilde{W}_{k,i}$ in (3) we have from (11) and (3) of [19]

$$\begin{aligned}
E[|\tilde{I}_{k,i} + \tilde{W}_{k,i}|^2] &= E[|\tilde{I}_{k,i}|^2] + E[|\tilde{W}_{k,i}|^2] \\
&= 8\sigma_H^4 N_t (N_r - 1) + 2\sigma_W^2 \\
&= \sigma_{\tilde{I}'}^2 \quad (\text{say}).
\end{aligned} \quad (12)$$

Now, each element of $\mathbf{S}^p$ in (1) carries $1/(2N_{rt})$ bits of information [19]. Therefore, each element of $\tilde{\mathbf{R}}_k$ also carries $1/(2N_{rt})$ bits of information. Hence, the average signal to interference plus noise ratio per bit of $\tilde{R}_{k,i}$ in (3) is defined as, using (5), (9) and (12)

$$\begin{aligned}
\text{SINR}_{av,b} &= \frac{E[|\tilde{F}_{k,i,i} S_i|^2] \times 2N_{rt}}{E[|\tilde{I}_{k,i} + \tilde{W}_{k,i}|^2]} \\
&= \frac{8\sigma_H^4 N_t (N_t + 1) \times 2N_{rt}}{8\sigma_H^4 N_t (N_r - 1) + 2\sigma_W^2}.
\end{aligned} \quad (13)$$

When $\sigma_W^2 = 0$ in (13), we get the upper bound on $\text{SINR}_{av,b}$ as given below

$$\begin{aligned}
\text{SINR}_{av,b,UB} &= \frac{8\sigma_H^4 N_t (N_t + 1) \times 2N_{rt}}{8\sigma_H^4 N_t (N_r - 1)} \\
&= \frac{2N_{rt} (N_t + 1)}{N_r - 1}.
\end{aligned} \quad (14)$$

The information contained in $\mathbf{S}^p$ in (1) is $N_r/(2N_{rt})$ bits. Hence the spectral efficiency of the precoded system is

$$\eta^p = \frac{N_r}{2N_{rt}} \quad \text{bits per transmission.} \quad (15)$$

Note that both (14) and (15) need to be as large as possible to minimize the BER and maximize the spectral efficiency. Let

$$N_{tot} = N_t + N_r. \quad (16)$$

Define

$$\begin{aligned}
f(N_t) &= \text{SINR}_{av,b,UB} + \eta^p \\
&= \frac{2N_{rt} (N_t + 1)}{N_r - 1} + \frac{N_r}{2N_{rt}} \\
&= \frac{2N_{rt} (N_t + 1)}{N_{tot} - N_t - 1} + \frac{N_{tot} - N_t}{2N_{rt}}
\end{aligned} \quad (17)$$

where we have used (16). We need to find N_t such that $f(N_t)$ is maximized. The plot of $\text{SINR}_{av,b,UB}$ (red curve), η^p (blue curve) and $f(N_t)$ (green curve), as a

function of N_t , keeping N_{tot} fixed, is depicted in Figs. 3 and 4. Note that $\text{SINR}_{\text{av},b,\text{UB}}$ increases monotonically and η^p decreases monotonically, with increasing N_t . We also find that $f(N_t)$ has a minimum (not maximum) at

$$N_t = N_{\text{tot}} - 2N_{rt}\sqrt{N_{\text{tot}}} - 1 \quad (18)$$

which is obtained by differentiating $f(N_t)$ in (17) with respect to N_t and setting the result to zero. Therefore,

the only possible solution is to avoid the minimum. Clearly we require $\text{SINR}_{\text{av},b,\text{UB}} > \ln(2)$, since it is the minimum average SNR per bit required for error-free transmission over any type of channel [19]. We also require $\eta^p > \eta_{\text{min}}^p$, where η_{min}^p is chosen by the system designer. Thus, we arrive at a range of the number of transmit antennas ($N_{t,\text{min}} \leq N_t \leq N_{t,\text{max}}$) that can be used, as shown in Fig. 3 and 4. Note that in Fig. 4(b) the minimum of $f(N_t)$ cannot be avoided, since η_{min}^p would be too small.

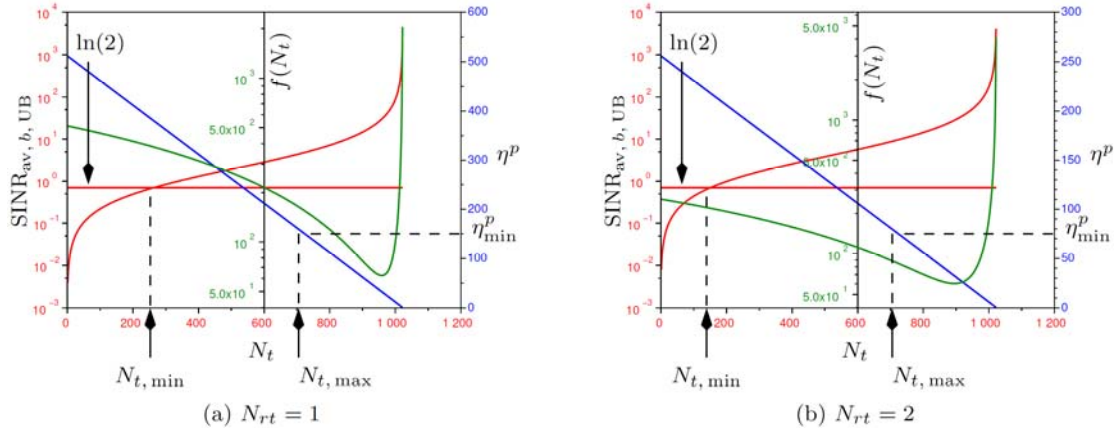


Fig. 3. $\text{SINR}_{\text{av},b,\text{UB}}$ and η^p as a function of N_t for $N_{\text{tot}} = 1024$, with precoding.

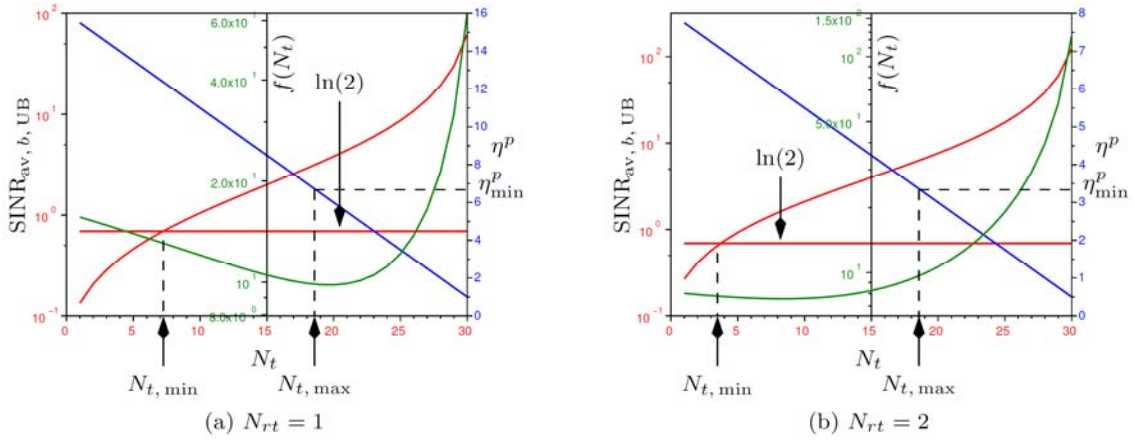


Fig. 4. $\text{SINR}_{\text{av},b,\text{UB}}$ and η^p as a function of N_t for $N_{\text{tot}} = 32$, with precoding.

Next, similar to (20) in [19], consider

$$\begin{aligned} \tilde{Y}_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{R}_{k,i} \\ &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} (\tilde{F}_{k,i} S_i + \tilde{I}_{k,i} + \tilde{W}_{k,i}) \\ &= F_i S_i + \tilde{U}_i \quad \text{for } 1 \leq i \leq N_r \end{aligned} \quad (19)$$

where $\tilde{R}_{k,i}$ is given by (3), F_i is real-valued and

$$\begin{aligned} F_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{F}_{k,i} \\ \tilde{U}_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} (\tilde{I}_{k,i} + \tilde{W}_{k,i}) \\ &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{U}_{k,i}' \quad (\text{say}). \end{aligned} \quad (20)$$

Since $\tilde{F}_{k,i}$ and $\tilde{U}_{k,i}'$ are statistically independent over re-transmissions (k), we have

$$\begin{aligned}
E[F_i^2] &= \frac{1}{N_{rt}^2} E \left[\sum_{k=0}^{N_{rt}-1} \tilde{F}_{k,i,i} \sum_{n=0}^{N_{rt}-1} \tilde{F}_{n,i,i} \right] \\
&= \frac{4\sigma_H^4 N_t [N_t + 1 + N_t(N_{rt} - 1)]}{N_{rt}} \\
&= \frac{4\sigma_H^4 N_t (N_t N_{rt} + 1)}{N_{rt}} \quad (21)
\end{aligned}$$

$$\begin{aligned}
E[|\tilde{U}_i|^2] &= \frac{\sigma_{U'}^2}{N_{rt}} \\
&= \frac{8\sigma_H^4 N_t (N_r - 1) + 2\sigma_W^2}{N_{rt}}
\end{aligned}$$

where we have used (5), (7), (12) and the fact that

$$E[\tilde{U}_{k,i}'] = 0 \quad (22)$$

where $\tilde{U}_{k,i}'$ is defined in (20). Next, we compute the average SINR per bit for $\tilde{Y}_i$ in (19). Note that since $\tilde{Y}_i$ is a “combination” of N_{rt} re-transmissions, its information content is $N_{rt}/(2N_{rt}) = 1/2$ bit (recall that the information content of $\tilde{R}_{k,i}$ in (19), is $1/(2N_{rt})$ bits). Therefore

$$\begin{aligned}
\text{SINR}_{\text{av},b,c} &= \frac{E[|F_i S_i|^2] \times 2}{E[|\tilde{U}_i|^2]} \\
&= \frac{8\sigma_H^4 N_t (N_t N_{rt} + 1) \times 2}{8\sigma_H^4 N_t (N_r - 1) + 2\sigma_W^2} \quad (23)
\end{aligned}$$

where the subscript “C” denotes “after combining” and we have used (9) and (21). Note that we prefer to use the word “combining” rather than averaging, since it is more appropriate in terms of the “information content” in $\tilde{Y}_i$. Once again with $\sigma_W^2 = 0$ and $N_t N_{rt} \gg 1$ we get the approximate upper bound on $\text{SINR}_{\text{av},b,c}$ as

$$\begin{aligned}
\text{SINR}_{\text{av},b,c,\text{UB}} &= \frac{8\sigma_H^4 N_t (N_t N_{rt} + 1) \times 2}{8\sigma_H^4 N_t (N_r - 1)} \\
&\approx \frac{2N_{rt} N_t}{N_r - 1} \\
&\approx \text{SINR}_{\text{av},b,\text{UB}} \quad (24)
\end{aligned}$$

when $N_t \gg 1$. Thus, the upper bound on the average SINR per bit before and after combining are nearly identical. Observe that re-transmitting the data increases the upper bound on the average SINR per bit, it does not improve the BER performance, which is seen in Section 5. After concatenation, the signal $\tilde{Y}_i$ in (19) for $0 \leq i \leq L_d - 1$ is sent to the turbo decoder. The details of turbo decoding will not be discussed here.

4. No Precoding

The block diagram of the system without precoding is similar to Fig. 1 in [19], excepting that now there are

N_t transmit and N_r receive antennas. The i^{th} element of $\tilde{\mathbf{H}}_k^H \tilde{\mathbf{R}}_k$, where $\tilde{\mathbf{R}}_k$ is given by (2), is (similar to (10) of [19])

$$\tilde{Y}_{k,i} = \tilde{F}_{k,i,i} S_i + \tilde{I}_{k,i} + \tilde{V}_{k,i} \quad \text{for } 1 \leq i \leq N_t \quad (25)$$

where

$$\begin{aligned}
\tilde{V}_{k,i} &= \sum_{j=1}^{N_r} \tilde{H}_{k,j,i}^* \tilde{W}_{k,j} \\
\tilde{I}_{k,i} &= \sum_{j=1}^{N_t} \tilde{F}_{k,i,j} S_j \\
\tilde{F}_{k,i,j} &= \sum_{l=1}^{N_r} \tilde{H}_{k,l,i}^* \tilde{H}_{k,l,j}
\end{aligned} \quad (26)$$

It can be shown that

$$E[\tilde{F}_{k,i,i}^2] = 4\sigma_H^4 N_r (N_r + 1). \quad (27)$$

We also have

$$E[\tilde{F}_{k,i,i}] = 2\sigma_H^2 N_r \quad (28)$$

And

$$\begin{aligned}
E[|\tilde{I}_{k,i}|^2] &= 8\sigma_H^4 N_r (N_t - 1) \\
E[|\tilde{V}_{k,i}|^2] &= 4\sigma_W^2 \sigma_H^2 N_r.
\end{aligned} \quad (29)$$

The total power of interference plus noise is

$$\begin{aligned}
E[|\tilde{I}_{k,i} + \tilde{V}_{k,i}|^2] &= E[|\tilde{I}_{k,i}|^2] + E[|\tilde{V}_{k,i}|^2] \\
&= 8\sigma_H^4 N_r (N_t - 1) \\
&\quad + 4\sigma_W^2 \sigma_H^2 N_r \\
&= \sigma_{U'}^2 \quad (\text{say}).
\end{aligned} \quad (30)$$

Observe that the total information emitted by N_t antennas per transmission is $N_t/(2N_{rt})$ bits. Therefore, the information contained in $\tilde{Y}_{k,i}$ in (25) is $N_t/(2N_{rt}N_t)$ bits. Hence, the average SINR per bit is

$$\begin{aligned}
\text{SINR}_{\text{av},b} &= \frac{E[|\tilde{F}_{k,i,i} S_i|^2] \times 2N_{rt}}{E[|\tilde{I}_{k,i} + \tilde{V}_{k,i}|^2]} \\
&= \frac{8\sigma_H^4 (N_r + 1) \times 2N_{rt}}{8\sigma_H^4 (N_t - 1) + 4\sigma_W^2 \sigma_H^2}
\end{aligned} \quad (31)$$

and for $\sigma_W^2 = 0$ we get the upper bound on SINR per bit as

$$\text{SINR}_{\text{av},b,\text{UB}} = \frac{(N_r + 1) \times 2N_{rt}}{N_t - 1}. \quad (32)$$

The spectral efficiency without precoding is

$$\eta = \frac{N_t}{2N_{rt}} \quad \text{bits per transmission.} \quad (33)$$

Define

$$\begin{aligned}
 f(N_t) &= \text{SNR}_{av,b,UB} + \eta \\
 &= \frac{2N_{rt}(N_r + 1)}{N_t - 1} + \frac{N_t}{2N_{rt}} \\
 &= \frac{2N_{rt}(N_{tot} - N_t + 1)}{N_t - 1} + \frac{N_t}{2N_{rt}}
 \end{aligned} \quad (34)$$

where N_{tot} is given by (16). The value of N_t that minimizes $f(N_t)$ in (34) is given by

$$N_t = 2N_{rt}\sqrt{N_{tot}} + 1. \quad (35)$$

Thus, we can arrive at a range of transmit antennas that can be used, avoiding the minimum of $f(N_t)$. This is illustrated in Figs. 5 and 6.

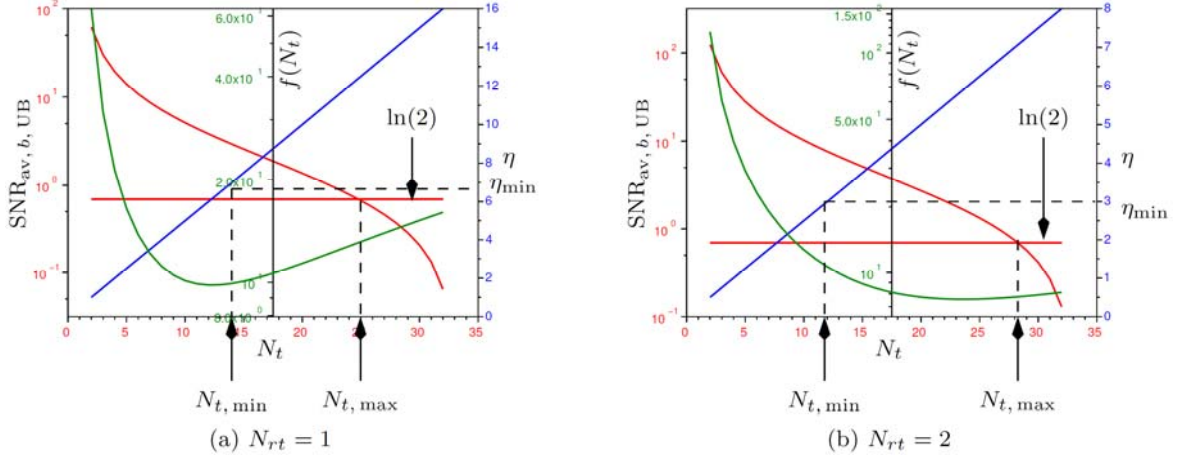


Fig. 5. $\text{SNR}_{av,b,UB}$ and η as a function of N_t for $N_{tot} = 32$, without precoding.

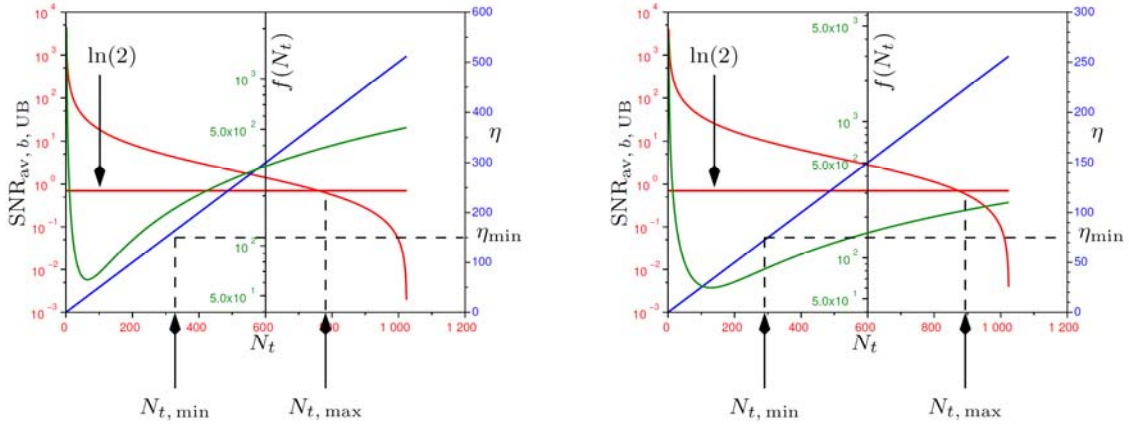


Fig. 6. $\text{SNR}_{av,b,UB}$ and η as a function of N_t for $N_{tot} = 1024$, without precoding.

Again similar to (20) in [19], we compute the average of $\tilde{Y}_{k,i}$ over all re-transmissions, as given by

$$\begin{aligned}
 \tilde{Y}_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{Y}_{k,i} \\
 &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} (\tilde{F}_{k,i} S_i + \tilde{I}_{k,i} + \tilde{V}_{k,i}) \\
 &= F_i S_i + \tilde{U}_i \quad \text{for } 1 \leq i \leq N_t
 \end{aligned} \quad (36)$$

where $\tilde{Y}_{k,i}$ is given by (25) and

$$\begin{aligned}
 F_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{F}_{k,i} \\
 \tilde{U}_i &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} (\tilde{I}_{k,i} + \tilde{V}_{k,i}) \\
 &= \frac{1}{N_{rt}} \sum_{k=0}^{N_{rt}-1} \tilde{U}_{k,i}' \quad (\text{say}).
 \end{aligned} \quad (37)$$

Since $\tilde{F}_{k,i}$ and $\tilde{U}_{k,i}'$ are statistically independent over re-transmissions (k), we have

$$\begin{aligned}
E[F_i^2] &= \frac{1}{N_{rt}^2} E \left[\sum_{k=0}^{N_{rt}-1} \tilde{F}_{k,i,i} \sum_{n=0}^{N_{rt}-1} \tilde{F}_{n,i,i} \right] \\
&= \frac{4\sigma_H^4 N_r [N_r + 1 + N_r(N_{rt} - 1)]}{N_{rt}} \\
&= \frac{4\sigma_H^4 N_r (N_r N_{rt} + 1)}{N_{rt}} \quad (38) \\
E[|\tilde{U}_i|^2] &= \frac{\sigma_{U'}^2}{N_{rt}} \\
&= \frac{8\sigma_H^4 N_r (N_t - 1) + 4\sigma_W^2 \sigma_H^2 N_r}{N_{rt}}
\end{aligned}$$

where we have used (27), (28) and (30) and the fact that

$$E[\tilde{U}_{k,i}'] = 0 \quad (39)$$

where $\tilde{U}_{k,i}'$ is defined in (37).

Noting that the average information content of $\tilde{Y}_i$ in (36) is $1/2$ bit, the average SINR per bit of $\tilde{Y}_i$ is

$$\begin{aligned}
\text{SINR}_{\text{av},b,c} &= \frac{E[|F_i S_i|^2] \times 2}{E[|\tilde{U}_i|^2]} \quad (40) \\
&= \frac{8\sigma_H^2 (N_r N_{rt} + 1) \times 2}{8\sigma_H^2 (N_t - 1) + 4\sigma_W^2}
\end{aligned}$$

where the subscript “C” denotes “after combining” and we have used (9) and (38). When $\sigma_W^2 = 0$ and $N_r N_{rt} \gg 1$, we get the upper bound as

$$\begin{aligned}
\text{SINR}_{\text{av},b,c,\text{UB}} &= \frac{8\sigma_H^2 (N_r N_{rt} + 1) \times 2}{8\sigma_H^2 (N_t - 1)} \quad (41) \\
&\approx \frac{2N_{rt} N_r}{N_t - 1} \\
&\approx \text{SINR}_{\text{av},b,\text{UB}}
\end{aligned}$$

for $N_r \gg 1$. Note that re-transmissions increases the upper bound on the average SINR per bit, it does not improve the BER.

5. Simulation Results

In this section, we discuss the results from computer simulations.

For the precoded case, the length of the data bits per “frame” (L_{d1}) is taken to be the smallest integer greater than 1000, which is an integer multiple of N_r . For the case without precoding, the length of the data bits per “frame” (L_{d1}) is taken to be the smallest integer greater than 1000, which is an integer multiple of N_t . Note that (see Figs. 1 and 2)

$$L_d = 2L_{d1}. \quad (42)$$

The simulations were carried out over 10^4 frames. The turbo encoder is given by (38) of [19]. Figure 7

gives the bit-error-rate (BER) results with precoding, whereas Fig. 8 gives the BER performance without precoding.

- Fig. 7(a) gives the bit-error-rate (BER) results for a 1×1 single input single output (SISO) system ($N_{\text{tot}} = 2$) with precoding. We get a BER of 2×10^{-2} at an average SNR per bit of 3.5 dB, with $N_{rt} = 4$. The corresponding spectral efficiency is $\eta^p = 1/8$ bits per transmission. The BER also does not vary significantly with the number of re-transmissions (N_{rt}).

- Fig. 7(b) gives the results for $N_{\text{tot}} = 32$ and different combinations of transmit (N_t) and receive (N_r) antennas. We find that the BER is quite insensitive to variations in N_t , N_r and N_{rt} . Moreover, the BER at an SNR per bit of 3.5 dB is about 2×10^{-6} , which is a significant improvement over the SISO system. Of all the curves, $N_t = 25$, $N_{rt} = 2$ gives the lowest spectral efficiency of $\eta^p = 1.75$ bits/sec/Hz and highest $\text{SNR}_{\text{av},b,\text{UB}} = 12.39$ dB. Of all the curves, $N_t = 12$, $N_{rt} = 1$ gives the highest spectral efficiency $\eta^p = 10$ bits/sec/Hz and lowest $\text{SNR}_{\text{av},b,\text{UB}} = 1.36$ dB.

- Fig. 7(c) gives the results for $N_{\text{tot}} = 1024$ for various combinations of N_t , N_r and N_{rt} . The BER is similar to that of $N_{\text{tot}} = 32$. Of all the curves, $N_t = 400$, $N_{rt} = 1$ gives the highest spectral efficiency of $\eta^p = 312$ bits/sec/Hz and lowest $\text{SNR}_{\text{av},b,\text{UB}} = 1.09$ dB. Of all the curves, $N_t = 1023$, $N_{rt} = 2$ gives the lowest spectral efficiency of $\eta^p = 0.25$ and highest $\text{SNR}_{\text{av},b,\text{UB}} \rightarrow \infty$.

- Fig. 8(a) gives the bit-error-rate (BER) results for a 1×1 single input single output (SISO) system ($N_{\text{tot}} = 2$) without precoding. We get a BER of 10^{-1} at an average SNR per bit of 3.5 dB, with $N_{rt} = 4$. The corresponding spectral efficiency is $\eta = 1/8$ bits per transmission. Compared to Fig. 3(a) of [19], we find that the BER varies significantly with the number of re-transmissions (N_{rt}) in Fig. 8(a) of this work. However, it must be noted that the definition of $\text{SNR}_{\text{av},b}$ in (23) of [19] and $\text{SINR}_{\text{av},b}$ (converted to decibels) in (31) of this work, are different. Comparing (23) of [19] and (31) (converted to decibels) in this work for $N_t = N_r = 1$, we find that (31) is 3 dB higher. This explains the 3 dB difference between Fig. 3(a) of [19] and Fig. 8(a) of this work.

- Fig. 8(b) gives the results for $N_{\text{tot}} = 32$ and different combinations of transmit (N_t) and receive (N_r) antennas. We find that the BER is quite insensitive to variations in N_t , N_r and N_{rt} . Moreover, the BER at an SNR per bit of 3.5 dB is about 10^{-6} , which is a significant improvement over the SISO system and similar to the precoded system of Fig. 7(b). Of all the curves, $N_t = 7$, $N_{rt} = 2$ gives the lowest spectral efficiency of $\eta = 1.75$ bits/sec/Hz and highest $\text{SNR}_{\text{av},b,\text{UB}} = 12.39$ dB. Of all the curves, $N_t = 16$, $N_{rt} = 1$ gives the highest spectral efficiency equal to $\eta = 8$ bits/sec/Hz and lowest $\text{SNR}_{\text{av},b,\text{UB}} = 5.4$ dB.

- Fig. 8(c) gives the results for $N_{\text{tot}} = 1024$ for various combinations of N_t , N_r and N_{rt} . The BER is similar to that of $N_{\text{tot}} = 32$. Of all the curves,

$N_t = 512$, $N_{rt} = 1$ gives the highest spectral efficiency of $\eta = 256$ bits/sec/Hz and lowest $\text{SNR}_{\text{av},b,\text{UB}} = 3.03$ dB. Of all the curves, $N_t = 1$, $N_{rt} = 2$ gives the lowest spectral efficiency of $\eta = 0.25$ bits/sec/Hz and highest $\text{SNR}_{\text{av},b,\text{UB}} \rightarrow \infty$.

6. Conclusions

This work presents an elegant method for data detection in turbo-coded massive MIMO with and

without precoding. An ideal receiver is assumed. Simulation results show that the BER is quite insensitive to a wide range in the number of transmit antennas and re-transmissions, when the total number of antennas in the transmitter and receiver (N_{tot}) is large and kept constant. Thus, the spectral efficiency can be made as large as possible for a given BER and N_{tot} . Future work could be to simulate a realistic massive MIMO system with carrier and timing synchronization and channel estimation.

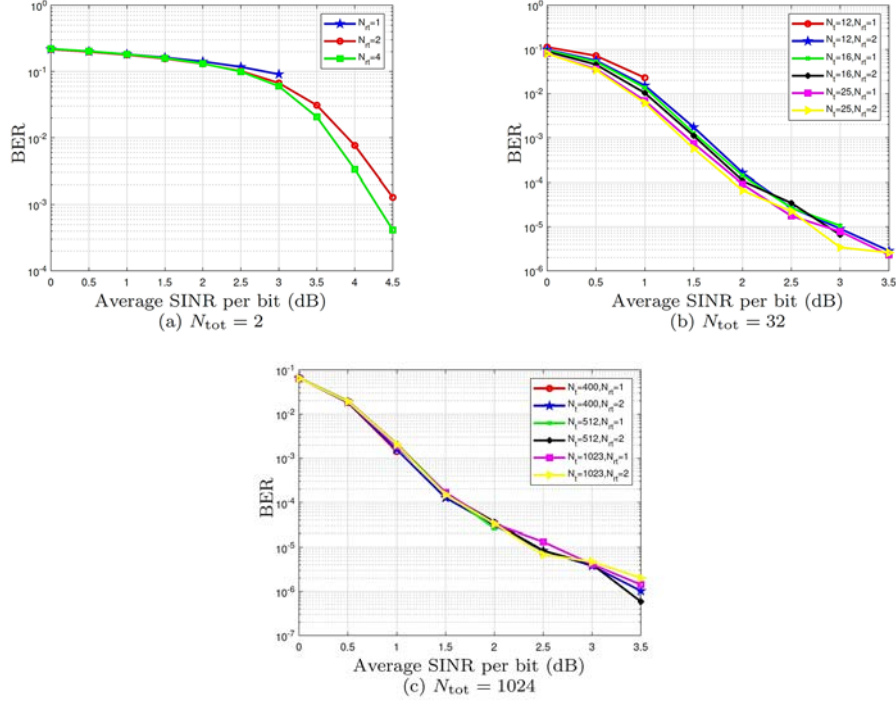


Fig. 7. Simulation results with precoding.

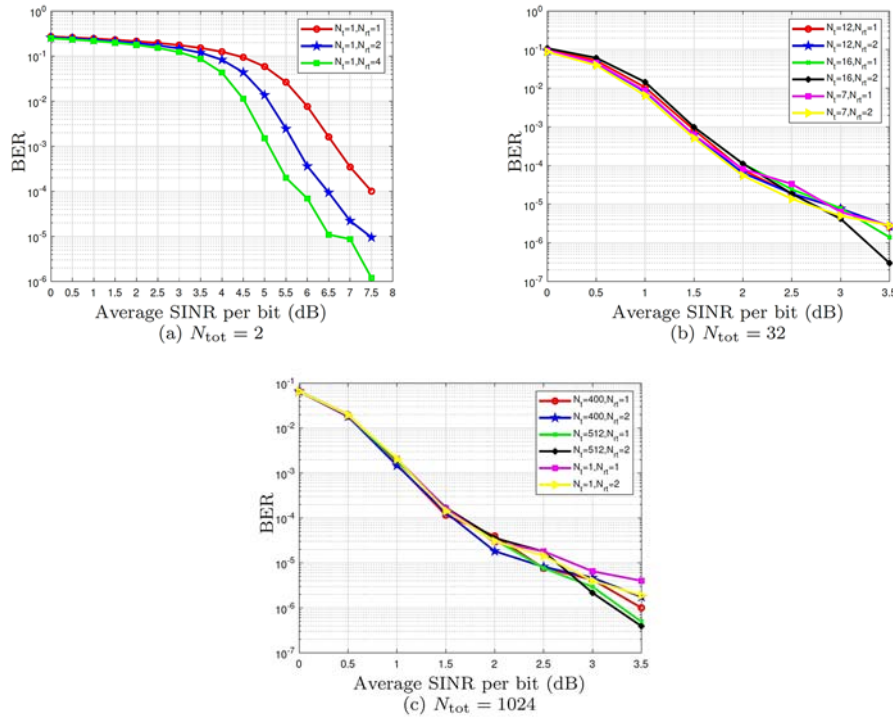


Fig. 8. Simulation results without precoding.

References

- [1]. S. A. Khwandah, J. P. Cosmas, and P. I. L. et. al., Massive MIMO systems for 5G communications, *Wireless Pers Commun.*, 120, 2021, pp. 2101–2115.
- [2]. H. Bergaoui, Y. Mlayeh, and F. Tlili, Adaptive pilot pattern for massive MIMO systems, *IEEE Access*, Vol. 9, 2021, pp. 81115–81124.
- [3]. J. Hoydis, F. A. Aoudia, A. Valcarce, and H. Viswanathan, Toward a 6G ai-native air interface, *IEEE Communications Magazine*, Vol. 59, No. 5, 2021, pp. 76–81.
- [4]. J. Tan and L. Dai, Wideband channel estimation for THz massive MIMO, *China Communications*, Vol. 18, No. 5, 2021, pp. 66–80.
- [5]. W. Ji, F. Zhang, and L. Qiu, Multipath extraction based ul/dl channel estimation for FDD massive MIMO-OFDM systems, *IEEE Access*, Vol. 9, 2021, pp. 75349–75361.
- [6]. S. Han, T. Xie, and C.-L. I, Greener physical layer technologies for 6G mobile communications, *IEEE Communications Magazine*, Vol. 59, No. 4, 2021, pp. 68–74.
- [7]. K. R. Jha and S. K. Sharma, Multifunctional Antennas for 4G/5G Communications and MIMO Applications, in Multifunctional Antennas and Arrays for Wireless Communication Systems (Eds. Satish K. Sharma, Jia-Chi S. Chieh), *John Wiley & Sons*, 2021, pp. 279–320.
- [8]. M. Belgiovine, K. Sankhe, C. Bocanegra, D. Roy, and K. R. Chowdhury, Deep learning at the edge for channel estimation in beyond-5G massive MIMO, *IEEE Wireless Communications*, Vol. 28, No. 2, 2021, pp. 19–25.
- [9]. C. Wu, X. Yi, Y. Zhu, W. Wang, L. You, and X. Gao, Channel prediction in high-mobility massive MIMO: From spatio-temporal autoregression to deep learning, *IEEE Journal on Selected Areas in Communications*, Vol. 39, No. 7, 2021, pp. 1915–1930.
- [10]. X. Liu, W. Chen, J. Chu, F. M. Ghannouchi, and Z. Feng, Multi-stream spatial digital predistortion for fully connected hybrid beamforming massive MIMO transmitters, *IEEE Transactions on Circuits and Systems I: Regular Papers*, Vol. 68, No. 7, 2021, pp. 2998–3011.
- [11]. A. D. Shoaie, D. T. Nguyen, and T. Le-Ngoc, A reconfigurable access scheme for massive-MIMO MTC networks, *IEEE Access*, Vol. 9, 2021, pp. 65547–65559.
- [12]. D. Wang, W. Zhang, and Q. Zhu, Heuristic search inspired beam selection algorithms for mmwave MU-MIMO system with discrete lens array, *IEEE Access*, Vol. 9, 2021, pp. 61324–61333.
- [13]. N. Jaglan, S. D. Gupta, and M. S. Sharawi, 18 element massive MIMO/diversity 5G smartphones antenna design for sub-6 GHz LTE bands 42/43 applications, *IEEE Open Journal of Antennas and Propagation*, Vol. 2, 2021, pp. 533–545.
- [14]. J. Wang, C.-X. Wang, J. Huang, H. Wang, and X. Gao, A general 3D space-time-frequency non-stationary THz channel model for 6G ultra-massive MIMO wireless communication systems, *IEEE Journal on Selected Areas in Communications*, Vol. 39, No. 6, 2021, pp. 1576–1589.
- [15]. V. M. T. Palhares, A. R. Flores, and R. C. de Lamare, Robust MMSE precoding and power allocation for cell free massive MIMO systems, *IEEE Transactions on Vehicular Technology*, Vol. 70, No. 5, 2021, pp. 5115–5120.
- [16]. J. Tan and L. Dai, Wideband beam tracking in THz massive MIMO systems, *IEEE Journal on Selected Areas in Communications*, Vol. 39, No. 6, 2021, pp. 1693–1710.
- [17]. F. Gao, B. Wang, C. Xing, J. An, and G. Y. Li, Wideband beamforming for hybrid massive MIMO terahertz communications, *IEEE Journal on Selected Areas in Communications*, Vol. 39, No. 6, 2021, pp. 1725–1740.
- [18]. K. Dovelos, M. Matthaiou, H. Q. Ngo, and B. Bellalta, Channel estimation and hybrid combining for wideband terahertz massive MIMO systems, *IEEE Journal on Selected Areas in Communications*, Vol. 39, No. 6, 2021, pp. 1604–1620.
- [19]. K. Vasudevan, K. Madhu, and S. Singh, Data Detection in Single User Massive MIMO Using Re-Transmissions, *The Open Signal Processing Journal*, Vol. 6, March. 2019, pp. 15–26.
- [20]. Scilab code for data detection in single user massive MIMO using re-transmissions, <https://www.codeocean.com/>, 6 2019.
- [21]. K. Vasudevan, S. Singh, and A. P. K. Reddy, Coherent receiver for turbo coded single-user massive MIMO-OFDM with retransmissions, in Multiplexing (S. Mohammady, Ed.), *IntechOpen*, London, 2019, Ch. 4, pp. 1–21.
- [22]. Scilab code for coherent receiver for turbo coded single-user massive MIMO-OFDM with retransmissions, <https://www.codeocean.com/>, 6, 2019.
- [23]. K. Vasudevan, A. Phani Kumar Reddy, G. K. Pathak, and S. Singh, On the probability of erasure for MIMO OFDM, *Semiconductor Science and Information Devices*, Vol. 2, No. 1, Apr. 2020, pp. 1–5.
- [24]. K. Vasudevan, A. P. K. Reddy, G. K. Pathak, and S. Singh, Scilab code for the probability of erasure for MIMO-OFDM, <https://www.codeocean.com/>, 4, 2020.
- [25]. K. Vasudevan, G. K. Pathak, and A. P. K. Reddy, Turbo Coded Single User Massive MIMO with Precoding, in *Proceedings of the 1st IFSA Winter Conference on Automation, Robotics & Communications for Industry 4.0 (ARCI' 2021)*, Chamonix-Mont-Blanc, February 2021, pp. 6–11.
- [26]. Scilab code for turbo coded single user massive MIMO with precoding, <https://www.codeocean.com/>, 2, 2021.
- [27]. K. Vasudevan, A. P. K. Reddy, S. Singh, and G. K. Pathak, Single user massive MIMO, *First Responder and Tactical Networks-3rd Workshop on 5G Technologies*, IEEE Future Networks, 2020.
- [28]. H. Sun, C. Ng, Y. Huo, R. Q. H. N. Wang, C.-M. Chen, K. Vasudevan, J. Yang, W. Montlouis, D. Ayanda, K. V. Mishra, K. Tekbiyik, and N. Hussain, Massive MIMO, *International Network Generations Roadmap-2021 Edition*, IEEE Future Networks, 2021.
- [29]. S. Schwarz, R. Heath, and M. Rupp, Single-user MIMO versus multi-user MIMO in distributed antenna systems with limited feedback, *EURASIP J. Adv. Signal Process.*, 2013, art. 54.
- [30]. R. W. Chang, Precoding for multiple-speed data transmission, *The Bell System Technical Journal*, Vol. 46, No. 7, Sep. 1967, pp. 1633–1649.
- [31]. S. Kasturia and J. M. Cioffi, Precoding for blocking signalling and shaped signal sets, in *Proceedings of the IEEE International Conference on Communications, World Prosperity through Communications*, Vol. 2, June 1989, pp. 1086–1090.
- [32]. G. J. Pottie and M. V. Eyuboglu, Combined coding and precoding for PAM and QAM HDSL systems, *IEEE*

- Journal on Selected Areas in Communications*, Vol. 9, No. 6, Aug 1991, pp. 861–870.
- [33]. A. K. Aman, R. L. Cupo, and N. A. Zervos, Combined trellis coding and DFE through Tomlinson precoding, *IEEE Journal on Selected Areas in Communications*, Vol. 9, No. 6, Aug 1991, pp. 876–884.
- [34]. G. D. Forney and M. V. Eyuboglu, Combined equalization and coding using precoding, *IEEE Communications Magazine*, Vol. 29, No. 12, December 1991, pp. 25–34.
- [35]. M. V. Eyuboglu and G. D. Forney, Trellis precoding: combined coding, precoding and shaping for intersymbol interference channels, *IEEE Transactions on Information Theory*, Vol. 38, No. 2, 1992, pp. 301–314.
- [36]. R. Laroia, S. A. Tretter, and N. Farvardin, A simple and effective precoding scheme for noise whitening on intersymbol interference channels, *IEEE Transactions on Communications*, Vol. 41, No. 10, 1993, pp. 1460–1463.
- [37]. H. W. Bode, Variable equalizers, *The Bell System Technical Journal*, Vol. 17, No. 2, 1938, pp. 229–244.
- [38]. S. U. H. Qureshi, Adaptive equalization, *Proceedings of the IEEE*, Vol. 73, No. 9, 1985, pp. 1349–1387.
- [39]. K. Vasudevan, Detection of signals in correlated interference using a predictive VA, in *Proceedings of the 8th International Conference on Communication Systems (ICCS 2002)*, Vol. 1, 2002, pp. 529–533.
- [40]. K. Vasudevan, Detection of signals in correlated interference using a predictive VA, *Signal Processing*, Vol. 84, No. 12, 2004, pp. 2271 – 2286.
- [41]. R. Koetter, A. C. Singer, and M. Tuchler, Turbo Equalization, *IEEE Sig. Proc. Mag.*, Vol. 21, No. 1, Jan. 2004, pp. 67–80.
- [42]. K. Vasudevan, Turbo Equalization of Serially Concatenated Turbo Codes using a Predictive DFE-based Receiver, *Signal, Image and Video Processing*, Vol. 1, No. 3, Aug. 2007, pp. 239–252.
- [43]. Digital Communications and Signal Processing, Second edition, *Universities Press*, Hyderabad, India, 2010.
- [44]. N. Fatema, G. Hua, Y. Xiang, D. Peng, and I. Natgunanathan, Massive MIMO linear precoding: A survey, *IEEE Systems Journal*, Vol. 12, No. 4, Dec 2018, pp. 3920–3931.
- [45]. S. Kim, Diversity order of precoding-aided spatial modulation using receive antenna selection, *Electronics Letters*, Vol. 56, No. 5, 2020, pp. 260–262.
- [46]. Transmit antenna selection for precoding-aided spatial modulation, *IEEE Access*, Vol. 8, 2020, pp. 40723– 40731.
- [47]. A. Haqiqatnejad, F. Kayhan, and B. Ottersten, Robust SINR-constrained symbol-level multiuser precoding with imperfect channel knowledge, *IEEE Transactions on Signal Processing*, Vol. 68, 2020, pp. 1837–1852.
- [48]. Q. Deng, X. Liang, X. Wang, M. Huang, C. Dong, and Y. Zhang, Fast converging iterative precoding for massive MIMO systems: An accelerated weighted Neumann series-steepest descent approach, *IEEE Access*, Vol. 8, 2020, pp. 50244–50255.
- [49]. Z. Li, C. Zhang, I. Lu, and X. Jia, Hybrid precoding using out-of-band spatial information for multi-user multi RF-chain millimeter wave systems, *IEEE Access*, Vol. 8, 2020, pp. 50872–50883.
- [50]. N. L. Johannsen, N. Peitzmeier, P. A. Hoeher, and D. Manteuffel, On the feasibility of multi-mode antennas in UWB and IoT applications below 10 GHz, *IEEE Communications Magazine*, Vol. 58, No. 3, 2020, pp. 69–75.
- [51]. K. Vasudevan, Coherent detection of turbo coded OFDM signals transmitted through frequency selective Rayleigh fading channels, in *Proceedings of the IEEE International Conference on Signal Processing, Computing and Control (ISPCC' 2013)*, September 2013, pp. 1–6.
- [52]. Scilab code for coherent detection of turbo coded OFDM signals transmitted through frequency selective Rayleigh fading channels, <https://www.codeocean.com/>, 7, 2019.
- [53]. Coherent detection of turbo-coded OFDM signals transmitted through frequency selective Rayleigh fading channels with receiver diversity and increased throughput, *Wireless Personal Communications*, Vol. 82, No. 3, 2015, pp. 1623–1642.
- [54]. Coherent turbo coded MIMO OFDM, in *Proceedings of the 12th International Conference on Wireless and Mobile Communications (ICWMC 2016)*, November 2016, pp. 91–99.
- [55]. Near capacity signaling over fading channels using coherent turbo coded OFDM and massive MIMO, *International Journal on Advances in Telecommunications*, Vol. 10, No. 1 & 2, 2017, pp. 22–37.
- [56]. A. Papoulis, Probability, Random Variables and Stochastic Processes, 3rd ed., *McGraw-Hill*, 1991.
- [57]. K. Vasudevan, Analog Communications: Problems & Solutions, *Ane Books*, 2018.





Automation, Robotics & Communications for Industry 4.0 (ARCI' 2022): 2nd IFSA Winter Conference

2-4 February 2022
Andorra la Vella, Andorra

About the Event

According to the modern market study, the global Industry 4.0 market is projected to grow from US \$ 116.14 billion in 2021 to US \$ 337.10 billion in 2028 at the CAGR of 16.4 % in the 2021-2028 period. The Industry 4.0 is an integrated system, which consists of an automation tool, robotic control, communications and big data analytics. The Industry 4.0 holds a lot of potentials and is expected to register a substantial growth in the near future. There are several conferences on automation, robotics and communications, but they are not meet the Industry 4.0 challenges. The series of annual ARCI Winter IFSA conferences have been launched to fill-in this gap and provide a forum for open discussion of state-of-the-art technologies related to control, automation, robotics and communication - main components of Industry 4.0.

The ARCI' 2022 conference will incorporate main fields covering research and development in a broaden range in automation, robotics, communication and data analyses, and united by the Industry 4.0 challenges. However it will be not a conference only about the future concepts and new visions. It will be also to discuss how to adopt the current R&D results for Industry 4.0 and to customize products under the conditions of highly flexible (mass-) production. The ARCI' 2022 conference is organized by the IFSA - one of the major professional, non-profit association serving for sensor industry and academy more than 20 years.

Industry 4.0:

- Design principles in Industry 4.0
- Industrial Big Data and Analytics
- Industrial Internet of Things (IoT)
- Smart Manufacturing and Technologies
- Smart Factories
- Smart Devices and Products
- Cyber-physical Systems
- Cloud Computing and Manufacturing
- Machine Learning and Artificial Intelligence in Manufacturing
- Digital Production and Virtual Engineering
- Soft Measurements

Automation:

- Automatic Control, Theory and Applications
- Linear/Nonlinear/Adaptive/Robust/Optimal Control
- Control Devices and Instruments
- Components and Technologies for Control
- Programmable Logic Controllers (PLC)
- Control System Modeling and Simulation
- Fuzzy-logic and Artificial Neural Networks in Control Systems
- Emerging Trends in Automation and Control Industry
- Industrial Automation and Control
- Manufacturing Systems and Automation
- Process Automation
- Process Control and Monitoring
- Optimal Control
- Telematics
- CAD / CAM / CIM / SCADA
- Computers for Control
- Computational Intelligence in Control
- Information Control in Manufacturing
- Intelligent Traffic Control
- Chemical Process Control
- Control in Agriculture Biological and Medical Systems
- Modeling and Control of Environmental Systems
- Artificial Intelligence for Cyber-Physical Systems in Automation
- Machine Learning in Control Applications
- Education and Training in Automatic Control and Systems

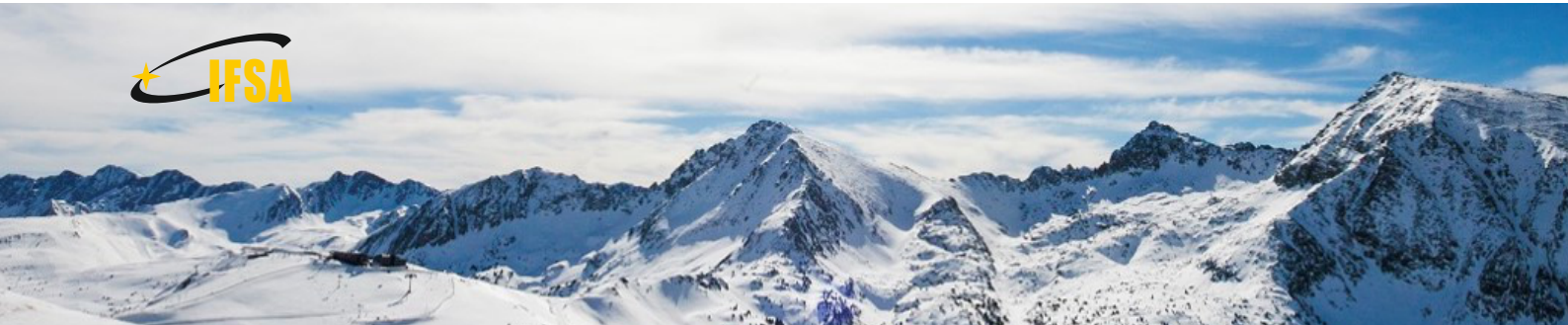
Robotics:

- Industrial Robots
- Soft Robots

- Biorobotics and Medical Robots
- Sensors for Robots
- Mobile Robots
- Humanoid Robots
- Human-Robot Interaction
- Rehabilitation robotics
- Intelligent Robots & Systems
- Mechatronic Systems
- Multimodality Human-machine Interaction
- Robot Control and Learning
- Cognitive Approach for Robotics
- Flexible Automation
- Emerging Trends in Robotics Industry
- Autonomous Systems and Drones
- Robots for Space Exploration
- Robotics in Defense
- Underwater Robots
- Network Robotics & Telerobotics
- Nanorobotics

Communications:

- Industrial Communication Technologies and Systems
- Emerging Trends in Communication Industry
- Industrial Networks and Automation
- Real-Time and Networked Embedded Systems
- Network Control and Security
- Web-enabled Manufacturing Control and Wireless Automation
- Wireless Sensor Networks for Robot Navigation
- Distributed Networks
- Network Architectures and Protocols
- Intelligent Network Components
- Next Generation Networks
- Communication Theory, Protocols and Signal Processing
- Telecommunications, Telemetry and Telecontrol
- Digital Telecommunications
- Telecommunications in Smart Cities
- Wireless and Mobile Communications
- 4G and 5G Mobile Communications Services
- Satellite and Space Communications
- Global Navigation Satellites Systems
- Sensor, Mesh, and Ad hoc Networks
- Underwater Sensor Networks
- Radio Communications Systems
- Energy Harvesting and Power Management Communication



Automation, Robotics & Communications for Industry 4.0 (ARCI' 2022): 2nd IFSA Winter Conference



Contribution Types:

- Keynote presentations
- Invited presentations
- Special sessions
- Regular sessions
- Poster sessions
- Industrial presentations
- Panel discussions and Round tables
- Exhibition

Organising Committee

Chairman:

Prof., Dr. Sergey Y. Yurish (IFSA, Spain)

Advisory Chairman:

Prof., Dr. Vijayakumar Varadarajan
(The University of New South Wales, Australia)

Conference and Publication Manager:

Mrs. Tetyana Zakharchenko
(IFSA Publishing, S. L., Spain)

Organizing Committee:

Mr. Javier Cañete (Universitat Politècnica de Catalunya
(UPC), Barcelona, Spain)
Mr. Luis Morey (Universitat Politècnica de Catalunya
(UPC), Barcelona, Spain)
Mr. Sergey Garmash (IFSA Publishing, S. L., Spain)

Deadlines:

Submission (2-page abstract):

Notification of acceptance:

Registration:

Camera ready (4-6 pages paper):

5 December 2021
in two weeks after submission
30 December 2021
15 January 2022

One event - three publications !

All abstracts will be published in the conference proceedings, which will be submitted for indexing to the Conference Proceedings Citation Index (CPCI) by Clarivate Analytics.

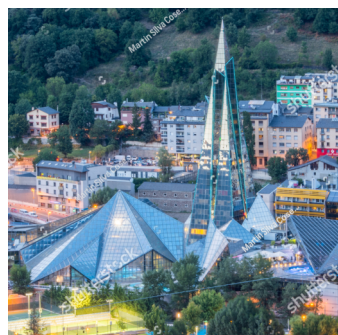
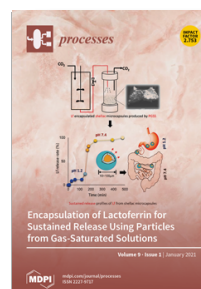
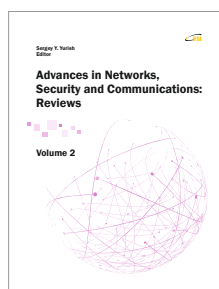
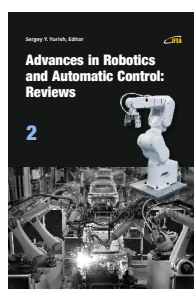


Authors will be invited to submit full-page extended papers to the special issues of Sensors & Transducers, MDPI Processes or MDPI Machines journals.

The limited number of full-page papers published in the journals will be selected to extend for book chapters for the Book Series on 'Advances in Robotics and Automatic Control: Reviews', Vol. 3 or 'Advances in Networks, Security and Communications: Reviews', Vol. 3. Both books will be submitted to the Book Citation Index by Clarivate Analytics.

Social Events:

- Welcome Cocktail
- Gala Dinner



Aims and Scope

Sensors & Transducers is established, international, peer-reviewed, open access journal (print and electronic). It provides the best platform for the researchers and scientist worldwide to exchange their latest findings and results in science and technology of physical, chemical sensors and biosensors. The journal publishes original results of scientific and research works related to strategic and applied studies in all aspects of sensors: reviews, regular research and application specific papers, and short notes. In comparison with other sensors related journals, which are mainly focused on technological aspects and sensing principles, the *Sensors & Transducers* significantly contributes in areas, which are not adequately addressed in other journals, namely: frequency (period), duty-cycle, time-interval, PWM, phase-shift, pulse number output sensors and transducers; sensor systems; digital, smart, intelligent sensors and systems designs; signal processing and ADC in sensor systems; advanced sensor fusion; sensor networks; applications, etc. By this way the journal significantly enriches the appropriate databases of knowledge.

Sensors & Transducers journal has a very high publicity. It is indexed and abstracted very quickly by Chemical Abstracts, EBSCO Publishing, ProQuest Science Journals, CAS Source Index (CASSI), Ulrich's Periodicals Directory, Google Scholar, etc. Since 2011 to 2014 *Sensors & Transducers* journal was covered and indexed by EI Compendex (CPX) index (including a Scopus, Embase, Engineering Village and Reaxys) in Elsevier products. The journal is included in the IFSA List of Recommended Journals (up-dated 9.12.2019), which contains only the best, established sensors related journals.

Topics of Interest

Include, but are not restricted to:

- Physical, chemical sensors and biosensors
- Digital, frequency, period, duty-cycle, time interval, PWM, pulse number output sensors and transducers
- Theory, principles, effects, design, standardization and modelling
- Smart sensors and systems
- Intelligent sensors and systems
- Sensor instrumentation
- Virtual instruments
- Sensors interfaces, buses and networks
- Signal processing, sensor fusion
- Remote sensing
- Frequency (period, duty-cycle)-to-code converters, ADC
- Technologies and materials
- Nanosensors and NEMS
- Microsystems
- Applications

Further information on this journal is available from the Publisher's web site:
http://www.sensorsportal.com/HTML/DIGEST/New_Digest.htm

Free Access and Subscriptions

Sensors & Transducers is the open access journal. All single articles are available for free download (article by article) without any registration and embargo period. For those who want to get the full page journal issue in print and/or pdf format there is an annual subscription. It includes 12 regular issues and some special issues. Annual subscription rates for 2020 are the following: Electronic version (in printable pdf format): 590.00 EUR; Printed with b/w illustrations: 950.00 EUR; 15 % discount is available for IFSA Members.

Further information about subscription is available on the IFSA Publishing's web site:
http://www.sensorsportal.com/HTML/DIGEST/Journal_Subscription.htm

Advertising Information

If you are interested in advertising or other commercial opportunities please contact by e-mail:
sales@sensorsportal.com

Instructions for Authors

http://www.sensorsportal.com/HTML/DIGEST/Guides_for_Authors.htm

Call for Chapters

Your Chapter may be in the next Volume of the popular Book Series

ADVANCES IN SENSORS: REVIEWS

8

Open Access Book Series

Since 2012



- Physical, chemical and biosensors
- Sensor uncertainty, accuracy, calibration
- Smart sensors and systems
- Intelligent sensors and systems
- Artificial Intelligence enabled sensors
- Virtual and soft sensors
- Sensor instrumentation
- Sensor buses and networks
- Signal processing, sensor fusion
- Nanosensors
- Photonic sensors
- Sensor interfacing and signal conditioning
- Materials for sensors
- MEMS, BioMEMS and NEMS
- Remote Sensors and Telemetry
- Sensor packages and reliability

https://www.sensorsportal.com/HTML/IFSA_Publishing.htm

