

ISSN 1726-5479

SENSORS & TRANSDUCERS

3 vol. 14-2
Special
/12



Physical and Chemical Sensors & Wireless Sensor Networks

International Frequency Sensor Association Publishing





Sensors & Transducers

Volume 14-2, Special Issue
March 2012

www.sensorsportal.com

ISSN 1726-5479

Editors-in-Chief: Sergey Y. Yurish, tel.: +34 93 413 7941, e-mail: editor@sensorsportal.com

Editors for Western Europe

Meijer, Gerard C.M., Delft University of Technology, The Netherlands
Ferrari, Vittorio, Università di Brescia, Italy

Editor for Eastern Europe

Sachenko, Anatoly, Ternopil State Economic University, Ukraine

Editors for North America

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

Editor South America

Costa-Felix, Rodrigo, Inmetro, Brazil

Editor for Africa

Maki K.Habib, American University in Cairo, Egypt

Editor for Asia

Ohyama, Shinji, Tokyo Institute of Technology, Japan

Editor for Asia-Pacific

Mukhopadhyay, Subhas, Massey University, New Zealand

Editorial Advisory Board

- Abdul Rahim, Ruzairi, Universiti Teknologi, Malaysia
Ahmad, Mohd Noor, Nothern University of Engineering, Malaysia
Annamalai, Karthigeyan, National Institute of Advanced Industrial Science and Technology, Japan
Arcega, Francisco, University of Zaragoza, Spain
Arguel, Philippe, CNRS, France
Ahn, Jae-Pyoung, Korea Institute of Science and Technology, Korea
Arndt, Michael, Robert Bosch GmbH, Germany
Ascoli, Giorgio, George Mason University, USA
Atalay, Selcuk, Inonu University, Turkey
Atghiaee, Ahmad, University of Tehran, Iran
Augutis, Vyantas, Kaunas University of Technology, Lithuania
Avachit, Patil Lalchand, North Maharashtra University, India
Ayes, Aladdin, De Montfort University, UK
Azamimi, Azian binti Abdullah, Universiti Malaysia Perlis, Malaysia
Bahreyni, Behraad, University of Manitoba, Canada
Baliga, Shankar, B., General Monitors Transnational, USA
Baoxian, Ye, Zhengzhou University, China
Barford, Lee, Agilent Laboratories, USA
Barlingay, Ravindra, RF Arrays Systems, India
Basu, Sukumar, Jadavpur University, India
Beck, Stephen, University of Sheffield, UK
Ben Bouzid, Sihem, Institut National de Recherche Scientifique, Tunisia
Benachaiba, Chellali, Universitaire de Bechar, Algeria
Binnie, T. David, Napier University, UK
Bischoff, Gerlinde, Inst. Analytical Chemistry, Germany
Bodas, Dhananjay, IMTEK, Germany
Borges Carval, Nuno, Universidade de Aveiro, Portugal
Bouchikhi, Benachir, University Moulay Ismail, Morocco
Bousbia-Salah, Mounir, University of Annaba, Algeria
Bouvet, Marcel, CNRS – UPMC, France
Brudzewski, Kazimierz, Warsaw University of Technology, Poland
Cai, Chenxin, Nanjing Normal University, China
Cai, Qingyun, Hunan University, China
Calvo-Gallego, Jaime, Universidad de Salamanca, Spain
Campanella, Luigi, University La Sapienza, Italy
Carvalho, Vitor, Minho University, Portugal
Cecelja, Franjo, Brunel University, London, UK
Cerde Belmonte, Judith, Imperial College London, UK
Chakrabarty, Chandan Kumar, Universiti Tenaga Nasional, Malaysia
Chakravorty, Dipankar, Association for the Cultivation of Science, India
Changhai, Ru, Harbin Engineering University, China
Chaudhari, Gajanan, Shri Shivaji Science College, India
Chavali, Murthy, N.I. Center for Higher Education, (N.I. University), India
Chen, Jiming, Zhejiang University, China
Chen, Rongshun, National Tsing Hua University, Taiwan
Cheng, Kuo-Sheng, National Cheng Kung University, Taiwan
Chiang, Jeffrey (Cheng-Ta), Industrial Technol. Research Institute, Taiwan
Chiriac, Horia, National Institute of Research and Development, Romania
Chowdhuri, Arijit, University of Delhi, India
Chung, Wen-Yaw, Chung Yuan Christian University, Taiwan
Corres, Jesus, Universidad Publica de Navarra, Spain
Cortes, Camilo A., Universidad Nacional de Colombia, Colombia
Courtois, Christian, Universite de Valenciennes, France
Cusano, Andrea, University of Sannio, Italy
D'Amico, Arnaldo, Università di Tor Vergata, Italy
De Stefano, Luca, Institute for Microelectronics and Microsystem, Italy
Deshmukh, Kiran, Shri Shivaji Mahavidyalaya, Barshi, India
Dickert, Franz L., Vienna University, Austria
Dieguez, Angel, University of Barcelona, Spain
Dighavkar, C. G., M.G. Vidyamandir's L. V.H. College, India
Dimitropoulos, Panos, University of Thessaly, Greece
Ding, Jianning, Jiangsu Polytechnic University, China
Djordjevic, Alexandar, City University of Hong Kong, Hong Kong
Donato, Nicola, University of Messina, Italy
Donato, Patricio, Universidad de Mar del Plata, Argentina
Dong, Feng, Tianjin University, China
Drljaca, Predrag, Intersema Sensoric SA, Switzerland
Dubey, Venketesh, Bournemouth University, UK
Enderle, Stefan, Univ. of Ulm and KTB Mechatronics GmbH, Germany
Erdem, Gursan K. Arzum, Ege University, Turkey
Erkmen, Aydan M., Middle East Technical University, Turkey
Estelle, Patrice, Insa Rennes, France
Estrada, Horacio, University of North Carolina, USA
Faiz, Adil, INSA Lyon, France
Fericean, Sorin, Balluff GmbH, Germany
Fernandes, Joana M., University of Porto, Portugal
Francioso, Luca, CNR-IMM Institute for Microelectronics and Microsystems, Italy
Francis, Laurent, University Catholique de Louvain, Belgium
Fu, Weiling, South-Western Hospital, Chongqing, China
Gaura, Elena, Coventry University, UK
Geng, Yanfeng, China University of Petroleum, China
Gole, James, Georgia Institute of Technology, USA
Gong, Hao, National University of Singapore, Singapore
Gonzalez de la Rosa, Juan Jose, University of Cadiz, Spain
Granel, Annette, Goteborg University, Sweden
Graff, Mason, The University of Texas at Arlington, USA
Guan, Shan, Eastman Kodak, USA
Guillet, Bruno, University of Caen, France
Guo, Zhen, New Jersey Institute of Technology, USA
Gupta, Narendra Kumar, Napier University, UK
Hadjiloucas, Sillas, The University of Reading, UK
Haider, Mohammad R., Sonoma State University, USA
Hashsham, Syed, Michigan State University, USA
Hasni, Abdelhafid, Bechar University, Algeria
Hernandez, Alvaro, University of Alcala, Spain
Hernandez, Wilmar, Universidad Politecnica de Madrid, Spain
Homontcovschi, Dorel, SUNY Binghamton, USA
Horstman, Tom, U.S. Automation Group, LLC, USA
Hsiai, Tzung (John), University of Southern California, USA
Huang, Jeng-Sheng, Chung Yuan Christian University, Taiwan
Huang, Star, National Tsing Hua University, Taiwan
Huang, Wei, PSG Design Center, USA
Hui, David, University of New Orleans, USA
Jaffrezic-Renault, Nicole, Ecole Centrale de Lyon, France
James, Daniel, Griffith University, Australia
Janting, Jakob, DELTA Danish Electronics, Denmark
Jiang, Liudi, University of Southampton, UK
Jiang, Wei, University of Virginia, USA
Jiao, Zheng, Shanghai University, China
John, Joachim, IMEC, Belgium
Kalach, Andrew, Voronezh Institute of Ministry of Interior, Russia
Kang, Moonho, Sunmoon University, Korea South
Kaniusas, Eugenijus, Vienna University of Technology, Austria
Katake, Anup, Texas A&M University, USA
Kausel, Wilfried, University of Music, Vienna, Austria
Kavasoglu, Nese, Mugla University, Turkey
Ke, Cathy, Tyndall National Institute, Ireland
Khelfaoui, Rachid, Université de Bechar, Algeria
Khan, Asif, Aligarh Muslim University, Aligarh, India
Kim, Min Young, Kyungpook National University, Korea South
Ko, Sang Choon, Electronics. and Telecom. Research Inst., Korea South
Kotulska, Malgorzata, Wroclaw University of Technology, Poland
Kockar, Hakan, Balikesir University, Turkey

Kong, Ing, RMIT University, Australia
Kratz, Henrik, Uppsala University, Sweden
Krishnamoorthy, Ganesh, University of Texas at Austin, USA
Kumar, Arun, University of Delaware, Newark, USA
Kumar, Subodh, National Physical Laboratory, India
Kung, Chih-Hsien, Chang-Jung Christian University, Taiwan
Lacnjevac, Caslav, University of Belgrade, Serbia
Lay-Ekuakille, Aime, University of Lecce, Italy
Lee, Jang Myung, Pusan National University, Korea South
Lee, Jun Su, Amkor Technology, Inc. South Korea
Lei, Hua, National Starch and Chemical Company, USA
Li, Fengyuan (Thomas), Purdue University, USA
Li, Genxi, Nanjing University, China
Li, Hui, Shanghai Jiaotong University, China
Li, Xian-Fang, Central South University, China
Li, Yuefa, Wayne State University, USA
Liang, Yuanchang, University of Washington, USA
Liawruangrath, Saisunee, Chiang Mai University, Thailand
Liew, Kim Meow, City University of Hong Kong, Hong Kong
Lin, Hermann, National Kaohsiung University, Taiwan
Lin, Paul, Cleveland State University, USA
Linderholm, Pontus, EPFL - Microsystems Laboratory, Switzerland
Liu, Aihua, University of Oklahoma, USA
Liu Changgeng, Louisiana State University, USA
Liu, Cheng-Hsien, National Tsing Hua University, Taiwan
Liu, Songqin, Southeast University, China
Lodeiro, Carlos, University of Vigo, Spain
Lorenzo, Maria Encarnacio, Universidad Autonoma de Madrid, Spain
Lukaszewicz, Jerzy Pawel, Nicholas Copernicus University, Poland
Ma, Zhanfang, Northeast Normal University, China
Majstorovic, Vidosav, University of Belgrade, Serbia
Malyshev, V.V., National Research Centre 'Kurchatov Institute', Russia
Marquez, Alfredo, Centro de Investigacion en Materiales Avanzados, Mexico
Matay, Ladislav, Slovak Academy of Sciences, Slovakia
Mathur, Prafull, National Physical Laboratory, India
Maurya, D.K., Institute of Materials Research and Engineering, Singapore
Mekid, Samir, University of Manchester, UK
Melnyk, Ivan, Photon Control Inc., Canada
Mendes, Paulo, University of Minho, Portugal
Mennell, Julie, Northumbria University, UK
Mi, Bin, Boston Scientific Corporation, USA
Minas, Graca, University of Minho, Portugal
Moghavvemi, Mahmoud, University of Malaya, Malaysia
Mohammadi, Mohammad-Reza, University of Cambridge, UK
Molina Flores, Esteban, Benemérita Universidad Autónoma de Puebla, Mexico
Moradi, Majid, University of Kerman, Iran
Morello, Rosario, University "Mediterranea" of Reggio Calabria, Italy
Mounir, Ben Ali, University of Sousse, Tunisia
Mrad, Nezih, Defence R&D, Canada
Mulla, Imtiaz Sirajuddin, National Chemical Laboratory, Pune, India
Nabok, Aleksey, Sheffield Hallam University, UK
Neelamegam, Periasamy, Sastra Deemed University, India
Neshkova, Milka, Bulgarian Academy of Sciences, Bulgaria
Oberhammer, Joachim, Royal Institute of Technology, Sweden
Ould Lahoucine, Cherif, University of Guelma, Algeria
Pamidighanta, Sayanu, Bharat Electronics Limited (BEL), India
Pan, Jisheng, Institute of Materials Research & Engineering, Singapore
Park, Joon-Shik, Korea Electronics Technology Institute, Korea South
Penza, Michele, ENEA C.R., Italy
Pereira, Jose Miguel, Instituto Politecnico de Seteбал, Portugal
Petsev, Dimitar, University of New Mexico, USA
Pogacnik, Lea, University of Ljubljana, Slovenia
Post, Michael, National Research Council, Canada
Prance, Robert, University of Sussex, UK
Prasad, Ambika, Gulbarga University, India
Prateepasen, Asa, Kingmoungut's University of Technology, Thailand
Pugno, Nicola M., Politecnico di Torino, Italy
Pullini, Daniele, Centro Ricerche FIAT, Italy
Pumera, Martin, National Institute for Materials Science, Japan
Radhakrishnan, S., National Chemical Laboratory, Pune, India
Rajanna, K., Indian Institute of Science, India
Ramadan, Qasem, Institute of Microelectronics, Singapore
Rao, Basuthkar, Tata Inst. of Fundamental Research, India
Raouf, Kosai, Joseph Fourier University of Grenoble, France
Rastogi Shiva, K., University of Idaho, USA
Reig, Candid, University of Valencia, Spain
Restivo, Maria Teresa, University of Porto, Portugal
Robert, Michel, University Henri Poincare, France
Rezazadeh, Ghader, Urmia University, Iran
Royo, Santiago, Universitat Politècnica de Catalunya, Spain
Rodriguez, Angel, Universidad Politécnica de Cataluña, Spain
Rothberg, Steve, Loughborough University, UK
Sadana, Ajit, University of Mississippi, USA
Sadeghian Marnani, Hamed, TU Delft, The Netherlands
Sapozhnikova, Ksenia, D.I.Mendeleyev Institute for Metrology, Russia
Sandacci, Serghei, Sensor Technology Ltd., UK
Saxena, Vibha, Bhabha Atomic Research Centre, Mumbai, India
Schneider, John K., Ultra-Scan Corporation, USA
Sengupta, Deepak, Advance Bio-Photonics, India
Seif, Selemeni, Alabama A & M University, USA
Seifter, Achim, Los Alamos National Laboratory, USA
Shah, Kriyang, La Trobe University, Australia
Sankarraj, Anand, Detector Electronics Corp., USA
Silva Girao, Pedro, Technical University of Lisbon, Portugal
Singh, V. R., National Physical Laboratory, India
Slomovitz, Daniel, UTE, Uruguay
Smith, Martin, Open University, UK
Soleymanpour, Ahmad, Damghan Basic Science University, Iran
Somani, Prakash R., Centre for Materials for Electronics Technol., India
Sridharan, M., Sastra University, India
Srinivas, Talabattula, Indian Institute of Science, Bangalore, India
Srivastava, Arvind K., NanoSonix Inc., USA
Stefan-van Staden, Raluca-Ioana, University of Pretoria, South Africa
Stefanescu, Dan Mihai, Romanian Measurement Society, Romania
Sumriddetchka, Sarun, National Electronics and Computer Technology Center, Thailand
Sun, Chengliang, Polytechnic University, Hong-Kong
Sun, Dongming, Jilin University, China
Sun, Junhua, Beijing University of Aeronautics and Astronautics, China
Sun, Zhiqiang, Central South University, China
Suri, C. Raman, Institute of Microbial Technology, India
Sysoev, Victor, Saratov State Technical University, Russia
Szewczyk, Roman, Industrial Research Inst. for Automation and Measurement, Poland
Tan, Ooi Kiang, Nanyang Technological University, Singapore
Tang, Dianping, Southwest University, China
Tang, Jaw-Luen, National Chung Cheng University, Taiwan
Teker, Kasif, Frostburg State University, USA
Thirunavukkarasu, I., Manipal University Karnataka, India
Thumbavanam Pad, Kartik, Carnegie Mellon University, USA
Tian, Gui Yun, University of Newcastle, UK
Tsiantos, Vassilios, Technological Educational Institute of Kaval, Greece
Tsigara, Anna, National Hellenic Research Foundation, Greece
Twomey, Karen, University College Cork, Ireland
Valente, Antonio, University, Vila Real, - U.T.A.D., Portugal
Vanga, Raghav Rao, Summit Technology Services, Inc., USA
Vaseashta, Ashok, Marshall University, USA
Vazquez, Carmen, Carlos III University in Madrid, Spain
Vieira, Manuela, Instituto Superior de Engenharia de Lisboa, Portugal
Vigna, Benedetto, STMicroelectronics, Italy
Vrba, Radimir, Brno University of Technology, Czech Republic
Wandelt, Barbara, Technical University of Lodz, Poland
Wang, Jiangping, Xi'an Shiyong University, China
Wang, Kedong, Beihang University, China
Wang, Liang, Pacific Northwest National Laboratory, USA
Wang, Mi, University of Leeds, UK
Wang, Shinn-Fwu, Ching Yun University, Taiwan
Wang, Wei-Chih, University of Washington, USA
Wang, Wensheng, University of Pennsylvania, USA
Watson, Steven, Center for NanoSpace Technologies Inc., USA
Weiping, Yan, Dalian University of Technology, China
Wells, Stephen, Southern Company Services, USA
Wolkenberg, Andrzej, Institute of Electron Technology, Poland
Woods, R. Clive, Louisiana State University, USA
Wu, DerHo, National Pingtung Univ. of Science and Technology, Taiwan
Wu, Zhaoyang, Hunan University, China
Xiu Tao, Ge, Chuzhou University, China
Xu, Lisheng, The Chinese University of Hong Kong, Hong Kong
Xu, Sen, Drexel University, USA
Xu, Tao, University of California, Irvine, USA
Yang, Dongfang, National Research Council, Canada
Yang, Shuang-Hua, Loughborough University, UK
Yang, Wuqiang, The University of Manchester, UK
Yang, Xiaoling, University of Georgia, Athens, GA, USA
Yaping Dan, Harvard University, USA
Ymeti, Aurel, University of Twente, Netherlands
Yong Zhao, Northeastern University, China
Yu, Haihu, Wuhan University of Technology, China
Yuan, Yong, Massey University, New Zealand
Yufera Garcia, Alberto, Seville University, Spain
Zakaria, Zulkarnay, University Malaysia Perlis, Malaysia
Zagnoni, Michele, University of Southampton, UK
Zamani, Cyrus, Universitat de Barcelona, Spain
Zeni, Luigi, Second University of Naples, Italy
Zhang, Minglong, Shanghai University, China
Zhang, Quintao, University of California at Berkeley, USA
Zhang, Weiping, Shanghai Jiao Tong University, China
Zhang, Wenming, Shanghai Jiao Tong University, China
Zhang, Xueji, World Precision Instruments, Inc., USA
Zhong, Haoxiang, Henan Normal University, China
Zhu, Qing, Fujifilm Dimatix, Inc., USA
Zorzano, Luis, Universidad de La Rioja, Spain
Zourob, Mohammed, University of Cambridge, UK

Contents

Volume 14-2
Special Issue
March 2012

www.sensorsportal.com

ISSN 1726-5479

Research Articles

Information Extraction from Wireless Sensor Networks: System and Approaches <i>Tariq Alsoubi, Abdelrahman Abuarqoub, Mohammad Hammoudeh, Zuhair Bandar, Andy Nisbet...</i>	1
Assessment of Software Modeling Techniques for Wireless Sensor Networks: A Survey <i>John Khalil Jacob, Ramiro Liscano, Jeremy S. Bradbury</i>	18
Effective Management and Energy Efficiency in Management of Very Large Scale Sensor Network <i>Moran Feldman, Sharoni Feldman</i>	47
Energy Efficient in-Sensor Data Cleaning for Mining Frequent Itemsets <i>Jacques M. Bahi, Abdallah Makhoul, Maguy Medlej</i>	64
IPv6 Routing Protocol for Low Power and Lossy Sensor Networks Simulation Studies <i>Leila Ben Saad, Cedric Chauvenet, Bernard Tourancheau</i>	79
Self-Powered Intelligent Sensor Node Concept for Monitoring of Road and Traffic Conditions <i>Sebastian Strache, Ralf Wunderlich and Stefan Heinen</i>	93
Variable Step Size LMS Algorithm for Data Prediction in Wireless Sensor Networks <i>Biljana Risteska Stojkoska, Dimitar Solev, Danco Davcev</i>	111
A Framework for Secure Data Delivery in Wireless Sensor Networks <i>Leonidas Perlepes, Alexandros Zaharis, George Stamoulis and Panagiotis Kikiras</i>	125
An Approach for Designing and Implementing Middleware in Wireless Sensor Networks <i>Ronald Beaubrun, Jhon-Fredy Llano-Ruiz, Alejandro Quintero</i>	150
Mobility Model for Self-Organizing and Cooperative MSN and MANET Systems <i>Andrzej Sikora and Ewa Niewiadomska-Szynkiewicz</i>	164
Evaluation of Hybrid Distributed Least Squares for Improved Localization via Algorithm Fusion in Wireless Sensor Networks <i>Ralf Behnke, Jakob Salzmann, Philipp Gorski, Dirk Timmermann</i>	179
An Effective Approach for Handling both Open and Closed Voids in Wireless Sensor Networks <i>Mohamed Aissani, Sofiane Bouznad, Abdelmalek Hariza and Salah-Eddine Allia</i>	196
Embedded Wireless System for Pedestrian Localization in Indoor Environments <i>Nicolas Fourty, Yoann Charlon, Eric Campo</i>	211
Neighbourtables – A Cross-layer Solution for Wireless CiNet Network Analysis and Diagnostics <i>Ismo Hakala and Timo Hongell</i>	228

The 6th International Conference on Sensor Technologies and Applications



SENSORCOMM 2012

19 - 24 August 2012 - Rome, Italy

Deadline for papers: 5 April 2012



Tracks: Architectures, protocols and algorithms of sensor networks - Energy, management and control of sensor networks - Resource allocation, services, QoS and fault tolerance in sensor networks - Performance, simulation and modelling of sensor networks - Security and monitoring of sensor networks - Sensor circuits and sensor devices - Radio issues in wireless sensor networks - Software, applications and programming of sensor networks - Data allocation and information in sensor networks - Deployments and implementations of sensor networks - Under water sensors and systems - Energy optimization in wireless sensor networks

<http://www.iaria.org/conferences2012/SENSORCOMM12.html>

The 3rd International Conference on Sensor Device Technologies and Applications



SENSORDEVICES 2012

19 - 24 August 2012 - Rome, Italy

Deadline for papers: 5 April 2012



Tracks: Sensor devices - Ultrasonic and Piezosensors - Photonics - Infrared - Geosensors - Sensor device technologies - Sensors signal conditioning and interfacing circuits - Medical devices and sensors applications - Sensors domain-oriented devices, technologies, and applications - Sensor-based localization and tracking technologies

<http://www.iaria.org/conferences2012/SENSORDEVICES12.html>

The 5th International Conference on Advances in Circuits, Electronics and Micro-electronics



CENICS 2012

19 - 24 August 2012 - Rome, Italy

Deadline for papers: 5 April 2012



Tracks: Semiconductors and applications - Design, models and languages - Signal processing circuits - Arithmetic computational circuits - Microelectronics - Electronics technologies - Special circuits - Consumer electronics - Application-oriented electronics

<http://www.iaria.org/conferences2012/CENICS12.html>

Structure Crack Identification Based on Surface-mounted Active Sensor Network with Time-Domain Feature Extraction and Neural Network

¹ Chunling DU, ¹ Jianqiang MOU, ¹ L. MARTUA, ¹ Shudong LIU, ¹ Bingjin CHEN, ¹ Jingliang ZHANG, ² F. L. LEWIS

¹A*STAR, Data Storage Institute, 5 Engineering Drive 1, Singapore 117608

²Automation and Robotics Research Institute, University of Texas, Arlington, TX76019, USA

E-mail: DU_Chunling@dsi.a-star.edu.sg

Received: 15 November 2011 / Accepted: 20 December 2011 / Published: 12 March 2012

Abstract: In this work the condition of metallic structures are classified based on the acquired sensor data from a surface-mounted piezoelectric sensor/actuator network. The structures are aluminum plates with riveted holes and possible crack damage at these holes. A 400 kHz sine wave burst is used as diagnostic signals. The combination of time-domain S0 waves from received sensor signals is directly used as features and preprocessing is not needed for the damage detection. Since the time sequence of the extracted S0 has a high dimension, principal component estimation is applied to reduce its dimension before entering NN (neural network) training for classification. An LVQ (learning vector quantization) NN is used to classify the conditions as healthy or damaged. A number of FEM (finite element modeling) results are taken as inputs to the NN for training, since the simulated S0 waves agree well with the experimental results on real plates. The performance of the classification is then validated by using these testing results. *Copyright © 2012 IFSA.*

Keywords: Active sensing network, Damage classification, Feature extraction, Lamb wave, Principal component analysis.

1. Introduction

To reduce the cost of maintenance, SHM (structural health monitoring) has been proposed as an alternative approach to replace traditional time-consuming inspection for maintenance. The wave propagation method for structural health monitoring has been demonstrated to be effective in detecting

debonding in composites and cracks in metallic structures. And early detection of such damages due to cyclic loads and environmental corrosion is critical for preventing catastrophic failure and prolonging the life of aircraft structures. Therefore, in this work, wave propagation method based on surface-mounted piezoelectric sensor arrays is adopted to monitor cracks at riveted holes.

In general, the structural health monitoring system consists of two major parts: hardware and software. The hardware includes the distributed sensor network and the data acquisition system. In this work, the active sensing network with actuators excited by known diagnosis signals is adopted. And the software part for diagnosis includes signal analysis for sensitive feature extraction and intelligent algorithms for damage interpretation and classification, which actually result in the physical condition of a given structure from the raw sensor measurements. Our research reported in this paper is concentrated on feature extraction and structure condition classification.

Neural network methods are widely used to solve classification problem, since when properly trained they easily map the extracted feature space to structure condition space. Designing an effective neural network has always been a challenging task. In [1], a three-layer probabilistic neural network is applied to classify the sensor data into several categories relative to the damage location in the circular plates using resonance frequency shifts of E/M (electro/mechanical) impedance as damage features. In [2], a backpropagation neural network is trained to categorize cracks according to their lengths using FE modeling data for scattering of ultrasound by the cracks emanating from rivet holes in a thin aluminum plate. An impedance-based damage detection combined with a back propagation neural network is developed in [3] to locate and identify the structure damages. In [4], with independent component analysis for vibration features, a multi-layer perceptron neural network, trained using an error back propagation algorithm, is able to detect the undamaged and damaged states with very good accuracy and repeatability.

Lamb wave [5, 10] is much more sensitive to structure damages than other structural responses such as modal shape, natural frequency, etc., and the artificial neural network technique based on Lamb wave testing is able to lead to precise identification of the damages. In [6], the authors developed an identification technique for debonding in adhesively bonded joints using Lamb wave signals interpreted by neural network training. In [7], different crack lengths at four locations in a PVC sandwich panel were numerically simulated and the percentage shifts in structural energy were used to train a backpropagation neural network. Good identification precision was achieved for another numerically simulated damage case, while poor precision was attained using measurement signals. In [8], the so-called DDFs (digital damage fingerprints) are extracted from the spectrographic characteristics of Lamb wave signals and serve as damage features. Various numerical simulation results are employed to train the neural network and then experimentally validated by identifying cylinder through-holes and delamination in the composite laminates. In most of these papers, the artificial neural network employs the method of supervised feedforward backpropagation.

This paper presents a method based on neural network for the classification of an aluminum plate with and without crack damage at riveted holes. The time-domain sensor signals are directly used as damage features without preprocessing, and key features having reduced data size are extracted after principal component estimation. The estimated key features are then considered as the input to the neural network, which is trained according to the learning vector quantization method. The neural network training mainly uses FEM data of Lamb wave propagation in the active sensor network system, and the classification performance is evaluated through the validation using the experimental testing data.

2. Active Sensing System for Structure Crack Detection

The aluminum plate with riveted holes illustrated in Fig. 1 is studied for crack detection using the active sensing system, which consists of sensors denoted as $s_1, s_2, \dots, s_7$, and actuators denoted as a_1, a_4 , and a_7 . The cracks at the hole are indicated in Fig. 1 with length l . The actuators excited by the diagnosis signal, which is the windowed sinewave burst as shown in Fig. 2, transmit the signal to the sensors. The received signal by the sensor contains the information about the integrity of the structure between the actuator and the sensor, and will be used to detect any crack occurrence by investigating any change in the received signal. Based on the analysis of the sensor signals, information can be retrieved concerning the extent of the damage and used to assess and classify the health condition of the structure. In this work, we take actuator a_4 as one case which is excited by the diagnosis signal in Fig. 2. It is mentioned that the distance between the sensor, the actuator and the hole, and the diagnostic signal frequency are determined with the help of analytical and numerical simulation, which is detailed in the accompanying paper [15].

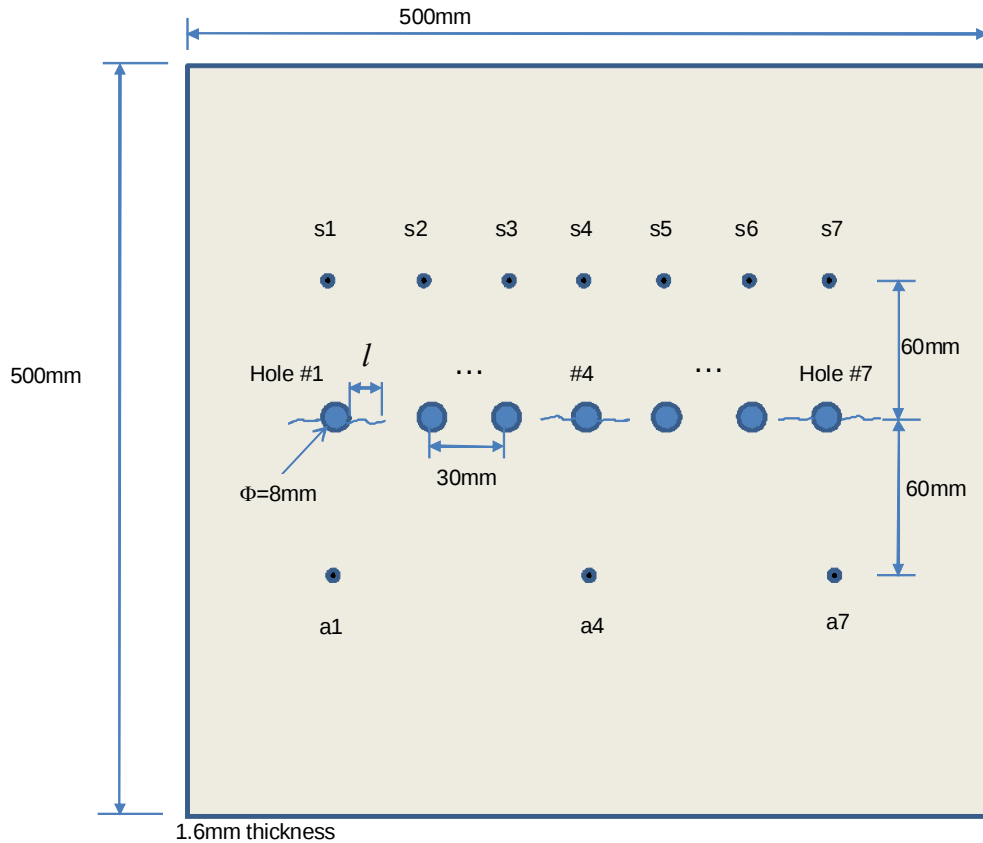


Fig. 1. Active sensing system for an aluminum plate with riveted holes with cracks.

The experimental testing setup consists of an Arbitrary Wave Generator (AWG) 2041, PZT driver, sensor signal amplifiers, and a programmable GAGE Compuscope 82G card connected to a PC running Labwindows/CVI. The actuation and the sensor signals are amplified by high bandwidth amplifiers. The data acquisition subsystem includes a PCI interface controlled with the PC running Labwindows/CVI, and the data are saved in PC through the GAGE card. The schematic diagram of the experimental setup is shown in Fig. 3.

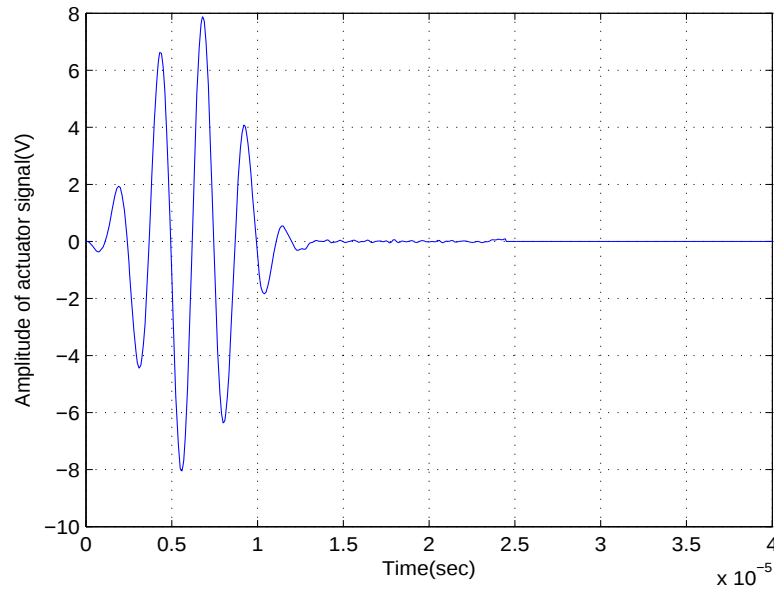


Fig. 2. 400 kHz sinewave burst injected to the actuator.

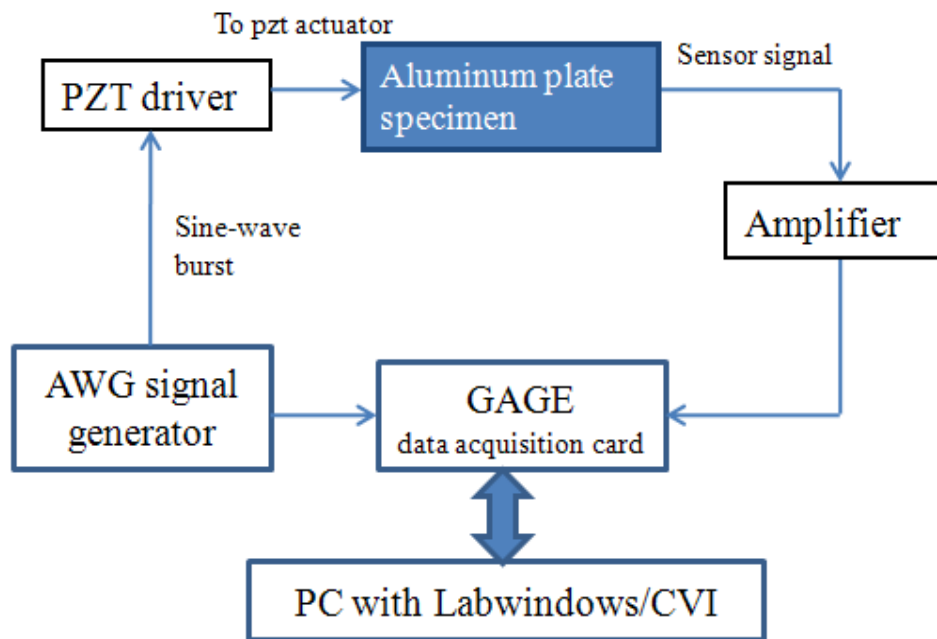


Fig. 3. Schematic diagram of experimental setup.

Experimental testing on real plates has been conducted. Circular transducers working as sensors and actuators are mounted to the surface of the plate using epoxy. The sensor signal is collected via the data acquisition card with 20 MHz sampling rate. As one example, the experimental sensor signals for the pristine plate are displayed in Fig. 4. We also take the plate with cracks $l = 6$ mm at hole #4 and $l = 2$ mm at hole #1 as another example for comparison. Fig. 5 shows the testing results, where the differences of S0 waves from those in Fig. 4 for the pristine plate are observable, e.g., the peak value is reduced, especially for s1 and s4. In next sections, we shall made use of these differences to detect the damage via feature extraction and condition classification.

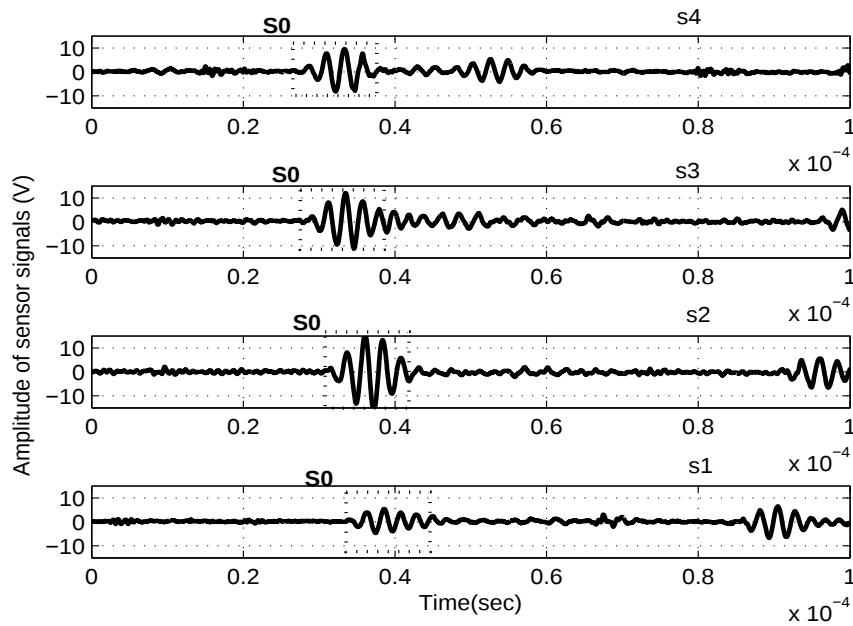


Fig. 4. Experimental sensor signals for the pristine plate.

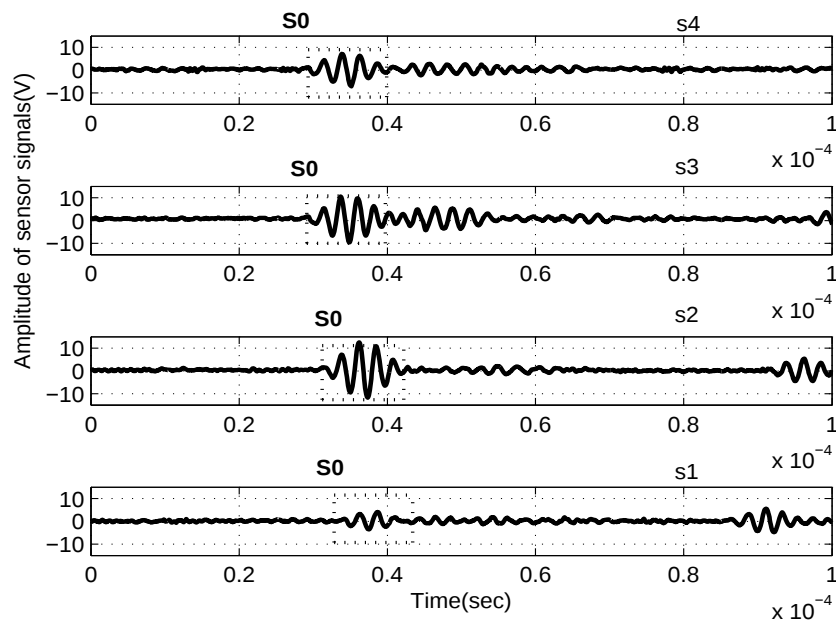


Fig. 5. Experimental sensor signals for the plate with cracks $l=6\text{mm}$ at hole #4 and $l=2\text{mm}$ at hole #1.

The classification architecture being used is shown in Fig. 6. The key steps involved in the methodology are 1) S0 wave extraction or feature extraction, 2) Estimation of principal components, 3) Structure condition classification using a neural network. The first step of the methodology involves the extraction of S0 wave. The time sequences of S0 waves from several sensors are used as inputs to the stage of principal component estimation. This step directly uses the time-domain signal of the sensors, which reduces the processing time for the sensor signals. The second step given in the proposed approach involves the dimension reduction of the sensor signal using Principal Component Estimation. The traditional method of singular value decomposition is used. The last and the main step of classifying structure conditions are obtained from the methodology of neural network. The neural network is based on LVQ nets. The LVQ network is trained using Kohonen learning rule to classify structure conditions.

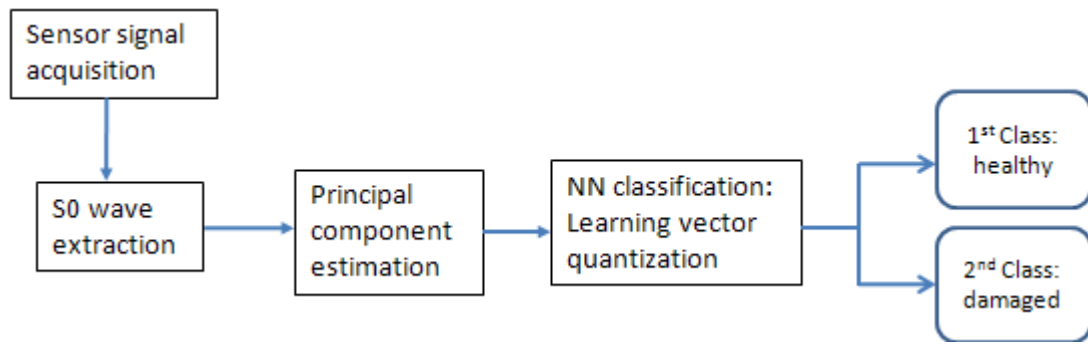


Fig. 6. Classification architecture.

3. Feature Extraction

To facilitate the NN training which needs sufficient sensor data, numerical data are desired to replace testing data from specimens in order to increase cost efficiency. For this purpose, verification of the numerical sensor signals is necessary to prove that they are reliable. Details about the simulation of the wave propagation for the system in Fig. 1 are seen in [15].

To normalize the simulation and the experiment data, a scaling is needed and can be determined according to the sensor data for the pristine plate. Fig. 7 shows the simulation result of sensor signals for the pristine plate. Similarly to the experimental result in Fig. 4, S0 wave is obviously fetched by the sensors. Also, for the plate with cracks $l=6$ mm at hole #4 and $l=2$ mm at hole #1, Fig. 8 shows its simulation results. It is noticed that S0 waves agree well in amplitude between the simulated and the experimental results, while a time shift is seen, which is due to the time shift of the excitation signals. Since the excitation signal is known, the time shift of the sensor signals is easily removed. After a thorough examination to 10 specimens, we believe that the FEM simulation can guarantee the reliability of S0 wave, which implies that the simulated S0 waves are believable and thus can be used to replace real testing data for the structure condition classification. So in the next section the features from the FEM results together with some of the experiment data will be used in the neural network training for damage classification.

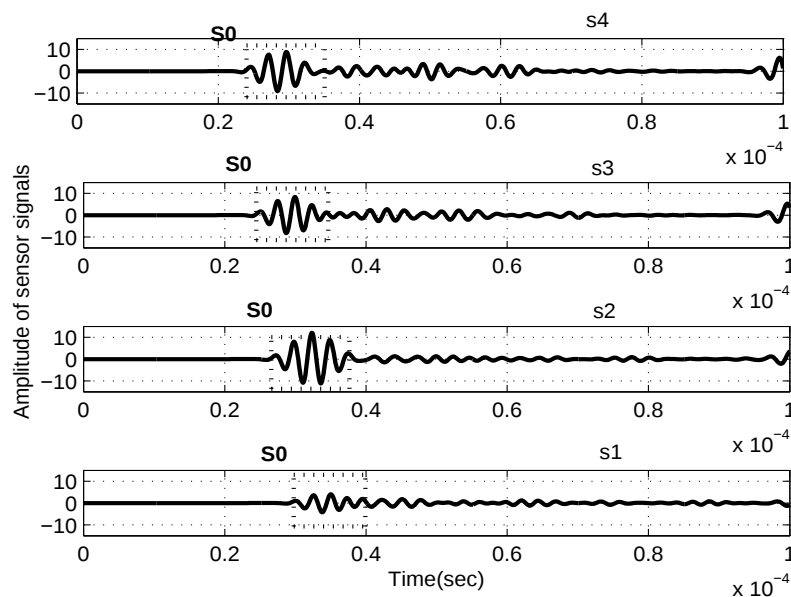


Fig. 7. Simulated sensor signals for the pristine plate.

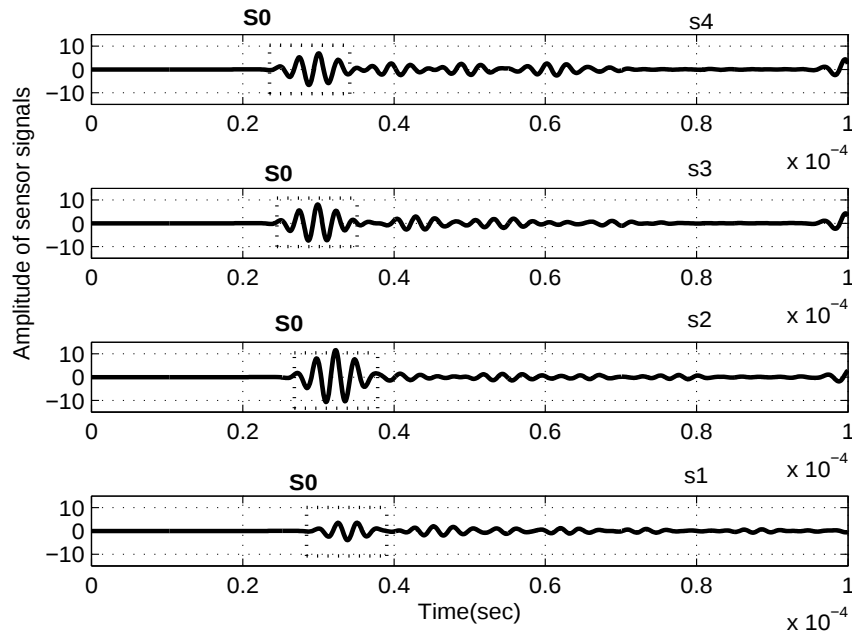


Fig. 8. Simulated sensor signals for the plate with cracks $l=6$ mm at hole #4 and $l=2$ mm at hole #1.

Next, we shall systematically analyze the relationship of the S0 wave with the crack length based on the simulated sensor data. With different crack lengths, the maximum amplitude of S0 wave of each sensor signal is plotted in Fig. 9. As expected, sensor s4 is most sensitive to crack at hole #4, which is seen from Fig. 9 as the curve corresponding to s4 drops most significantly even for a small crack $l=2$ mm. Other sensors s2 and s3 are sensitive to bigger cracks, while s1 signal does not change much and thus it is not able to detect the crack at hole #4.

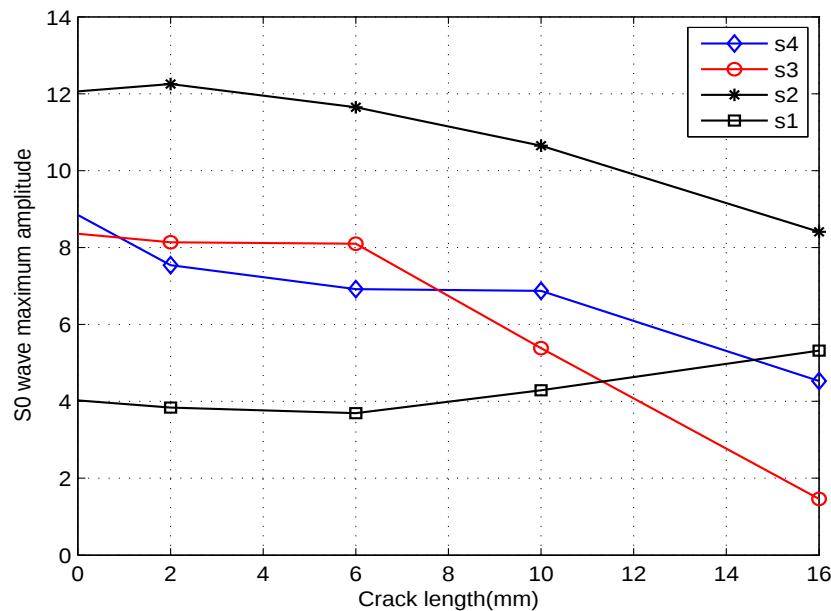


Fig. 9. Maximum amplitude of S0 wave versus crack length for crack at hole #4.

As for cracks located respectively at holes #3, #2 and #1, the S0 wave maximum amplitude versus different crack lengths is displayed in Figs. 10-12. In Fig. 10, s3 and s2 are most sensitive to cracks,

and s1 is also possibly useful to detect crack. In Fig. 11 for the crack at hole #2, s1 and s2 are able to detect it. However, in Fig. 12 for crack at hole #1, none of the four sensors is capable of detecting the crack. This implies that excitation to an actuator closer to it is required.

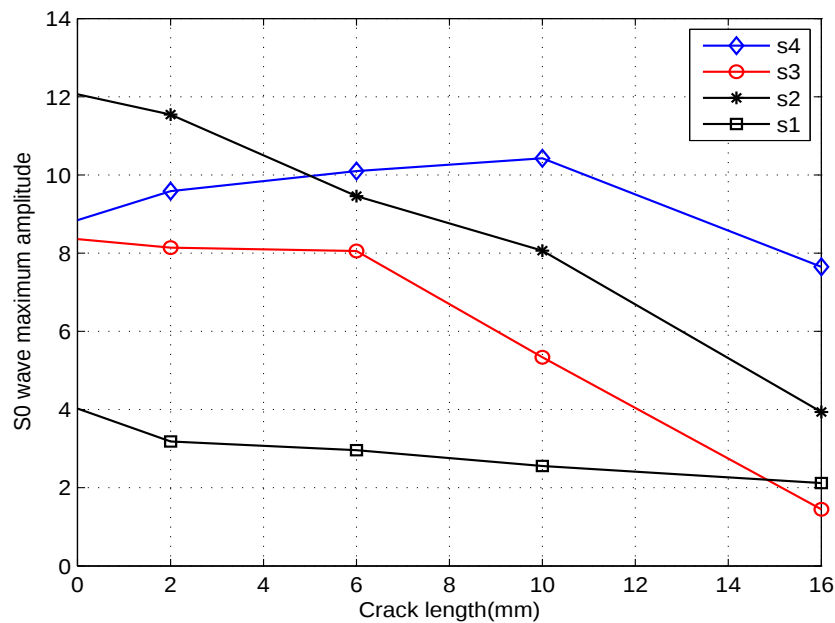


Fig. 10. Maximum amplitude of S0 wave versus crack length for crack at hole #3.

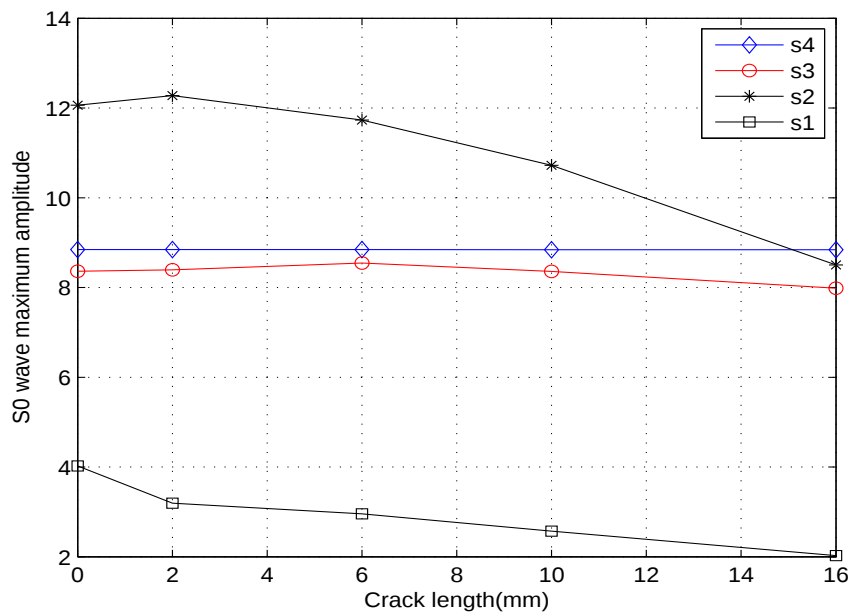


Fig. 11. Maximum amplitude of S0 wave versus crack length for crack at hole #2.

The above analysis shows that the sensors are all useful to crack detection. It is also noticed that S0 wave amplitude as well as its time delay (or, time of flight [11]) relative to actuator signal are sensitive to the crack. Therefore the time sequences of S0 waves of sensors s1-s4 will be used as features for classification in this paper. Take the crack at hole #4 as an example. The combined S0 wave time sequence of sensors s1-s4 is shown in Fig. 13.

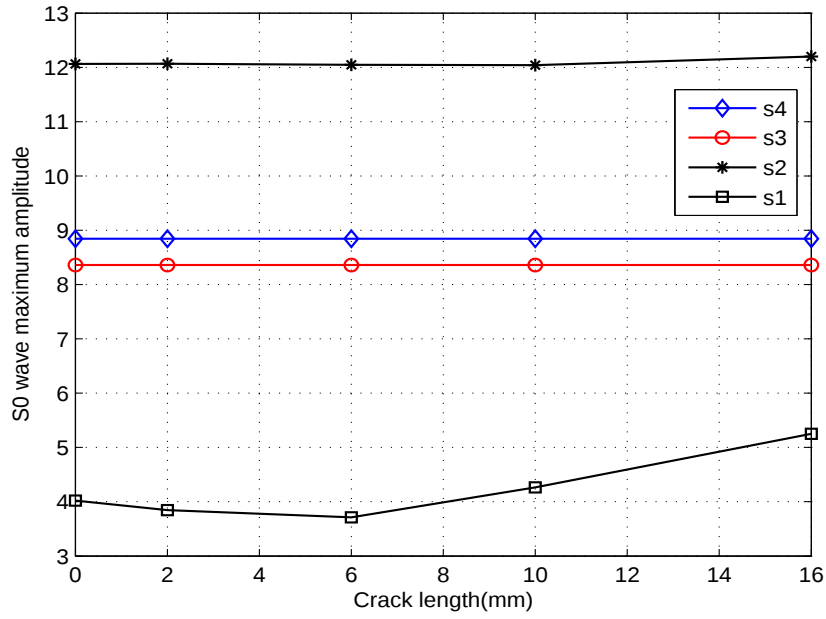


Fig. 12. Maximum amplitude of S0 wave versus crack length for crack at hole #1.

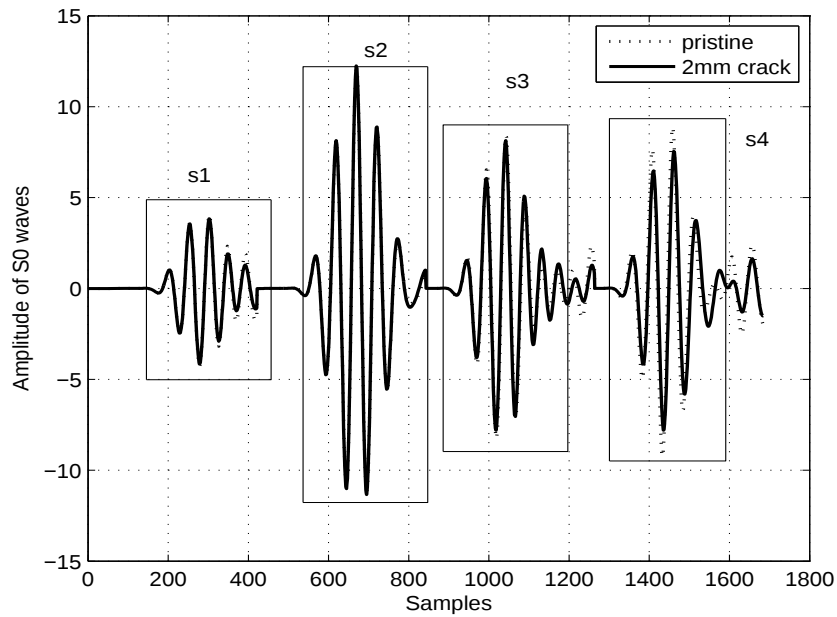


Fig. 13. S0 waves for crack at hole #4.

4. Principal Component Estimation

To make the damage classification simple, the time sequence of the S0 waves undergoes the principle component analysis so that the principal components are extracted. Principal component analysis (PCA) is a statistical technique used for data compression by determining a linear transformation matrix $W \in \mathbb{R}^{m \times n}$ ($m < n$). The data $X \in \mathbb{R}^{n \times 1}$ is compressed and a lower dimension data $y \in \mathbb{R}^{m \times 1}$ is yielded and given by

$$y = WX. \quad (1)$$

The PCA technique is to reduce the number of features representing a data by discarding the ones which have small variance and retains only those that have large variance. It uses singular value decomposition method in calculating the eigenvectors of the co-variance matrix formed by analyzing the sensor data. Only those eigenvectors are selected which give the maximum information about the data. These chosen eigenvectors form the matrix W . A very brief introduction to the standard principal components computation is given as follows.

Let the time sequence of S0 wave from each sensor signal be denoted as $s_k \in R^{M \times 1}$, $k = 1, \dots, N$. The total number of the sensors is N . All extracted S0 waves form a 1-D vector given by

$$c_i = \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_N \end{bmatrix}, \quad c \in R^{Q=MN}, \quad i = 1, \dots, L, \quad (2)$$

where the total number of the specimens participating in the principal component estimation is L . The mean of the S0 waves for all specimens is obtained as

$$\tau = \frac{1}{L} \sum_{i=1}^L c_i. \quad (3)$$

Subtracting the mean from the original data c_i yields

$$\tilde{c}_i = c_i - \tau. \quad (4)$$

The covariance matrix for the different specimens is obtained as

$$C = \sum_{i=1}^L \tilde{c}_i \tilde{c}_i^T = \Gamma \Gamma^T, \quad (5)$$

$$\Gamma = [\tilde{c}_1 \quad \tilde{c}_2 \quad \dots \quad \tilde{c}_L] \quad (6)$$

The eigenvectors corresponding to the covariance matrix C in (5) are computed in order to form the basis for the construction of W matrix in (1). The number of possible eigenvectors that would yield the maximum information about the dataset, is equal to the number of specimens in the training set. Therefore, for a dataset with L specimens, L eigenvectors are reasonably taken into account to form the W matrix. Consider a new matrix given by

$$G = \Gamma^T \Gamma \in R^{L \times L}, \quad (7)$$

and let the eigenvalue-eigenvector pairs of G be (μ_k, θ_k) ($k=1, \dots, L$). We have

$$G \theta_k = \mu_k \theta_k. \quad (8)$$

It is easily known that $\Gamma \theta_k$ are the eigenvectors of $C = \Gamma \Gamma^T$. Thus L eigenvectors are computed instead of computing Q eigenvectors. A transformation matrix W is then constructed for dimension reduction as follows.

$$W = \begin{bmatrix} (\Gamma \theta_1)^T \\ (\Gamma \theta_2)^T \\ \vdots \\ (\Gamma \theta_m)^T \end{bmatrix}, \quad m < L, \quad (9)$$

and correspondingly $\mu_1 > \mu_2 > \dots > \mu_m$. Therefore, $y = WX$ produces transformed input vectors y whose components are uncorrelated and ordered according to the magnitude of their variance. Those components that contribute only a small amount to the total variance in the data set are eliminated.

5. Damage Classification Using a Neural Network Method

In this section, a neural network is used to classify the structure conditions which are normal and abnormal. The output of the previously calculated principal components becomes the input to the neural network for training. The neural network is a learning vector quantization network which is shown in Fig. 14.

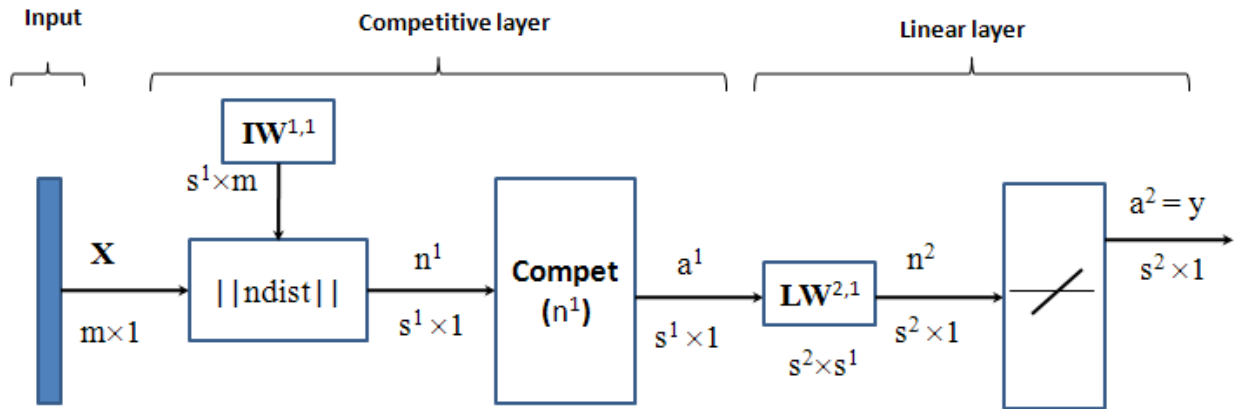


Fig. 14. LVQ network architecture.

5.1. LVQ Neural Network

The LVQ network is trained according to Kohonen learning rule [13]. The learning starts from a set of input and target pairs:

$$x_1, t_1; x_2, t_2; \dots; x_K, t_K. \quad (10)$$

Each target vector has a single 1. For example, for input vectors to be assigned to four classes,

$$t_K = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad (11)$$

means the corresponding x_k belongs to the second of four classes.

When the network is in training, the distance from an input x to each row of the input weight matrix $IW^{1,1}$ is computed with the function $ndist$. The hidden neurons of layer 1 compete. If the i^{th} element of n^1 is most positive, and the neuron i wins the competition. Then the competitive transfer function produces a 1 as the i^{th} element of a^1 , and all other elements of a^1 are zero. a^1 is then multiplied by the layer 2 weights $IW^{2,1}$, the single 1 in a^1 selects the class k^* associated with the input x . Thus the network has assigned the input vector x to class k^* and $a_{k^*}^2$ is 1. If the assignment is correct, the i^{th} row of $IW^{1,1}$ is adjusted in such a way to move this row closer to the input vector x , and if the assignment is not correct, the i^{th} row of $IW^{1,1}$ is adjusted to move the row away from x . Therefore, if x is classified correctly,

$$a_{k^*}^2 = t_{k^*} = 1, \quad (12)$$

the new value of the i^{th} row of $IW^{1,1}$ is computed as

$${}_iIW^{1,1}(q) = {}_iIW^{1,1}(q-1) + \alpha(p(q) - {}_iIW^{1,1}(q-1)). \quad (13)$$

If x is classified incorrectly,

$$a_{k^*}^2 = 1 \neq t_{k^*} = 0, \quad (14)$$

the new value of the i^{th} row of $IW^{1,1}$ is computed as

$${}_iIW^{1,1}(q) = {}_iIW^{1,1}(q-1) - \alpha(p(q) - {}_iIW^{1,1}(q-1)). \quad (15)$$

5.2. Classification Performance Analysis

In this section, we mainly would like to demonstrate the effectiveness of this kind of time-domain feature processed via principle component extraction in the crack detection with the implementation of neural network. As such, without loss of generality, cracks at holes #1 to #4 associated with sensors 1 to 4 are considered here. As is discussed in Section 3, the time domain data of S0 waves from sensors 1 to 4 are used as features to classify the plates into categories relative to the structure condition. In this paper, two classes are assigned: 1 representing no damage, and 2 representing damage with crack.

As shown in Table 1, the shaded parts are the types of plates under consideration. The data used for principal component estimation and neural network training mostly come from FEM results. Only one case is from a real specimen as the pristine plate. For principal component estimation and neural network training, these data are expanded as 1019 pristine plate and 736 damaged plates, which means the sensor data for pristine plate is used for 1019 times with random noise ($\leq 5\%$) added, and the sensor data for each damaged case is used for 46 times and also coupled with the random noise. The dimension of S0 wave combination from the four sensors is 1684. After principal component estimation, the dimension is reduced from 1684 to 13.

The LVQ neural network being used ('newlvq' function in Matlab) is a two-layer network. The first layer is a competitive layer that uses the compet transfer function and calculates the distance from an input to each row of the input weight matrix. The second layer is a linear layer having purelin neurons. In this application, the number of hidden neuron of the first layer is 4 and the class percentages are 45 % and 55 %.

As shown in Table 1, testing results from 10 real plates (indicated by the shadow) are used to verify the classification method. Based on the trained LVQ neural network, 8 plates are classified correctly, and 2 plates are not classified correctly. It is noted the NN training is mainly based on the FEM simulation results. The trained neural network leads to such a classification results for the tested specimens is acceptable and promising. It is also noticed that the trained neural network is potentially able to identify combined cracks, although the training is solely based on the single crack cases.

Table 1. Structure Condition classification results.

Plates	Crack length l (mm)	FEM simulation plates	Tested plates	Classification results
Pristine	0	T	T	1
	0			1
Crack at Hole #4	2	T		
	6	T		
	10	T		2
	16	T		2
Crack at Hole #3	2	T		2
	6	T		1
	10	T		2
	16	T		2
Crack at Hole #2	2	T		
	6	T		
	10	T		
	16	T		
Crack at Hole #1	2	T		
	6	T		
	10	T		
	16	T		
Cracks:2mm@hole#4, 6mm@hole#1				2
Cracks:6mm@hole#4, 2mm@hole#1				1

Classification results: 1- healthy; 2- damaged

T: used for principal component estimation and NN training

6. Conclusions

In this paper, the aluminum plates with the riveted holes and possible crack damage at these holes have been considered and the surface-mounted piezoelectric sensor/actuator network has been utilized to detect the crack. The 400 kHz sine wave burst has been used as the diagnostic signal and injected to the actuator and it propagates to sensors in order to detect the integrity of the plate. The combination of time-domain S0 waves from all sensitive sensor signals has been directly used as the feature to detect the crack damage. After the principal component estimation, the reduced-size data work as inputs for the LVQ neural network training. The neural network training has mainly relied on a number of FEM simulation results, since the simulated S0 wave agrees well with its experimental testing result on the real plate. The performance of the classification has been validated by using the testing results from 10 real plates, and it results in 8 plates classified correctly. The results imply that this time-domain feature processed with principle component extraction is straightforward and effective to identify the crack damage facilitated by the active sensing network.

References

- [1]. V. Giurgiutiu, *Structural Health Monitoring with Piezoelectric Wafer Active Sensors*, Academic Press/Elsevier, Burlington, MA, 2008.
- [2]. K. Zgonc, and J. D. Achenbach, A neural network for crack sizing trained by finite element calculations, *NDT and E International*, Vol. 29, No. 3, 1996, pp. 147-155.
- [3]. V. Lopes Jr. a, G. Park, H. H. Cudney, and D. J. Inman, Smart structures health monitoring using artificial neural network, in *Proceedings of the 2nd International Workshop on Structural Health Monitoring*, Stanford University, Stanford, CA, September 8-10, 1999, pp. 976-985.
- [4]. C. Zang, M. I. Friswell, and M. Imregun, Structure damage detection using independent component analysis, *Structural Health Monitoring*, Vol. 3, 2004, pp. 69-83.
- [5]. V. Giurgiutiu, Tuned Lamb wave excitation and detection with piezoelectric wafer active sensors for structural health monitoring, *Journal of Intelligent Material Systems and Structures*, 16, 2005, pp. 291-305.
- [6]. U. Bork, R. E. Challis, Artificial neural networks applied to Lamb wave testing of T-form adhered joints, In *Proc. of the Conference on the Inspection of Structural Composites*, 1994.
- [7]. L. H. Yam, Y. J. Yan, J. S. Jiang, Vibration-based damage detection for composite structures using wavelet transform and neural network identification, *Composite Structures*, 60, 2003, pp. 403-412.
- [8]. Z. Su, L. Ye, Lamb wave propagation-based damage identification for quasi-isotropic CF/EP composite laminates using artificial neural algorithm, part I: methodology and database development, *Journal of Intelligent Material Systems and Structures*, 16, 2003, pp. 97-111.
- [9]. L. Ye, Z. Su, C. Yang, Z. He, and X. Wang, Hierarchical development of training database for artificial neural network-based damage identification, *Composite Structures*, 76, 2006, pp. 224-233.
- [10]. J.-B. Ihn, and F. -K. Chang, Detection and monitoring of hidden fatigue crack growth using a built-in piezoelectric sensor/actuator network: I. Diagnostics, *Smart Materials and Structures*, Vol. 13, 2004, pp. 609-620.
- [11]. J.-B. Ihn, and F.-K. Chang, Detection and monitoring of hidden fatigue crack growth using a built-in piezoelectric sensor/actuator network: II. Validation using riveted joints and repair patches, *Smart Materials and Structures*, Vol. 13, 2004, pp. 621-630.
- [12]. P. Dang, H. Stephanou, F. Ham, and F. L. Lewis, Facial expression recognition using a two stage neural network, *Proceedings of the 15th Mediterranean Conference on Control and Automation*, Athens, Greece, 27-29 July, 2007.
- [13]. T. Kohonen, *Self-Organizing Maps*, Second Edition, Springer-Verlag, Berlin, 1997.
- [14]. Z. Su, L. Ye, and Y. Lu, Guided Lamb waves for identification of damage in composite structures: A review, *Journal of Sound and Vibration*, Vol. 295, 2006, pp. 753-780.
- [15]. J. Q. Mou, L. Martua, Y. Q. Yu, Z. M. He, C. L. Du, J. L. Zhang, and E. H. Ong, Structural health monitoring using PZT transducer network and Lamb waves, in *Proc. of the ASME 2010 International Mechanical Engineering Congress and Exposition, IMECE 2010*, Vancouver, British Columbia, Canada, 12-18 November 2010.

Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because of it is a peer reviewed international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per year by International Frequency Sensor Association (IFSA). In addition, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc. Since 2011 the journal is covered and indexed (including a Scopus, Embase, Engineering Village and Reaxys) in Elsevier products.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

- Physical, chemical and biosensors;
- Digital, frequency, period, duty-cycle, time interval, PWM, pulse number output sensors and transducers;
- Theory, principles, effects, design, standardization and modeling;
- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
- Signal processing;
- Frequency (period, duty-cycle)-to-digital converters, ADC;
- Technologies and materials;
- Nanosensors;
- Microsystems;
- Applications.

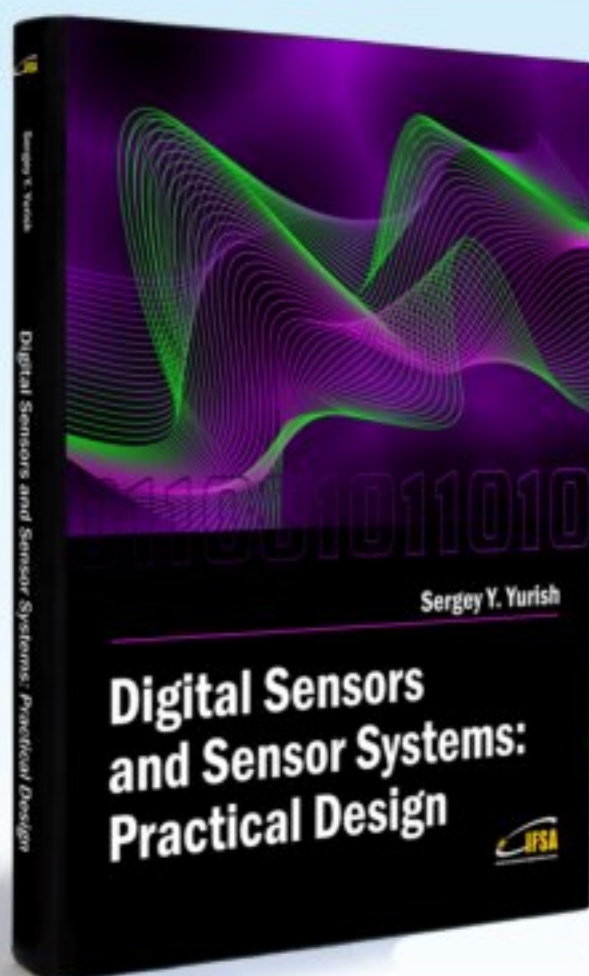
Submission of papers

Articles should be written in English. Authors are invited to submit by e-mail editor@sensorsportal.com 8-14 pages article (including abstract, illustrations (color or grayscale), photos and references) in both: MS Word (doc) and Acrobat (pdf) formats. Detailed preparation instructions, paper example and template of manuscript are available from the journal's webpage: <http://www.sensorsportal.com/HTML/DIGEST/Submission.htm> Authors must follow the instructions strictly when submitting their manuscripts.

Advertising Information

Advertising orders and enquires may be sent to sales@sensorsportal.com Please download also our media kit: http://www.sensorsportal.com/DOWNLOADS/Media_Kit_2012.pdf

Digital Sensors and Sensor Systems: Practical Design will greatly benefit undergraduate and at PhD students, engineers, scientists and researchers in both industry and academia. It is especially suited as a reference guide for practitioners, working for Original Equipment Manufacturers (OEM) electronics market (electronics/hardware), sensor industry, and using commercial-off-the-shelf components, as well as anyone facing new challenges in technologies, and those involved in the design and creation of new digital sensors and sensor systems, including smart and/or intelligent sensors for physical or chemical, electrical or non-electrical quantities.



"It is an outstanding and most completed practical guide about how to deal with frequency, period, duty-cycle, time interval, pulse width modulated, phase-shift and pulse number output sensors and transducers and quickly create various low-cost digital sensors and sensor systems ..." (from a review)

Order online:

http://www.sensorsportal.com/HTML/BOOKSTORE/Digital_Sensors.htm



www.sensorsportal.com