ISSN 1726-5479

SENSORS & TRANSDUCERS

vol. 143
8 /12

Sensors and Transducers Applications

International Frequency Sensor Association Publishing

IFSA

Sensors & Transducers

Volume 143, Issue 8
August 2012
www.sensorsportal.com
ISSN 1726-5479

Sensors & Transducers Journal (ISSN 1726-5479) is a peer review international journal published monthly online by International Frequency Sensor Association (IFSA).
Available in electronic and on CD.

Sensors & Transducers Journal

Contents

Volume 143
Issue 8
August 2012

www.sensorsportal.com

ISSN 1726-5479

Research Articles

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/Submition.htm

International Frequency Sensor Association (IFSA).

Sensors & Transducers Journal, Vol. 143, Issue 8, August 2012, pp. 79-87

Sensors & Transducers

ISSN 1726-5479

http://www.sensorsportal.com

A New Method for Linear Compression and Decompression of Sequential Sensor Signals

[1, 2,*] **Zhiqiang SUN,** [1,2]**Zhiyong LI**

[1] School of Energy Science and Engineering, Central South University, Changsha 410083, China

[2] Hunan Key Laboratory of Energy Conservation in Process Industry, Central South University, Changsha 410083, China

[*]E-mail: zqsun@csu.edu.cn

Received: 23 May 2012 /Accepted: 21 August 2012 /Published: 28 August 2012

Abstract: In this paper we bring forward a new linear method of lossy data compression aiming at effective and efficient utilization of sequential sensor signals. In the course of compression, the filtering and encapsulation are carried out first according to the signal type and the threshold value; second, the linear compression is conducted by comparing the maximum and minimum slopes of the sensor signal; third, the compressed signal is archived into the historical data storage zone for later use. Conversely, the signal is reconstructed by linear interpolation during the decompression process. The test results of a standard sinusoidal signal and a measured dynamic pressure signal show that the proposed method has higher compression ratio and less compression error than the spinning door transformation. It also reveals that this method is suitable for the compression and decompression of various types of sensor signals, especially for those containing massive data, multiple sampling, disturbance and redundancy. *Copyright © 2012 IFSA.*

Keywords: Sequential sensor signal, Lossy data compression, Linear interpolation, Compression ratio, Compression error.

1. Introduction

Accurate measurement and efficient utilization of sensor signals are of great importance to the process control in industry such as energy, power, metallurgy, etc. Sensor signals in process industry are usually sequential, massive, and high-frequency [1, 2]. Due to the huge amount of data, it has been one of the most difficult problems in practical applications to handle those signals in a real-time way. Thereby it is necessary to compress sensor signals to decrease storage space and speed up transmission efficiency.

Since sensor signals normally has time attribute, small-scale fluctuations hardly affect the history curve. Hence efficient compression of sensor signals can be achieved by lossy compression through discarding partial redundant data.

Investigations on the compression of sensor signals are intensive in recent years. Langen pointed out the importance and potential usage of sensor signals in nuclear power plants [3]. Hale and Sellers proposed the methods of box car and backward slope [4]. When processing the sensor signals with linear drifts and fluctuations, the compression ratio of box car was not satisfactory and the anti-noise ability was poor. Mah *et al* put forward a piecewise linear trending method, which could adjust the threshold value of compression errors automatically [5]. Gray conducted a systematical study on the method of vector quantization [6]. MacGregor and Kourti adopted the statistical method to achieve the compression of multivariable sensor signals [7]. Baksh and Stephanopoulos employed the wavelet method to extract time-domain characteristics and to discern process failure, and generalized the applications of wavelets to data compression in chemical industry [8–10]. Singha and Seborg analyzed the pattern matching problem in data compression, and concluded that the wavelet compression had the best pattern matching effect [12]. Imtiaz *et al* [12] compared the performance of spinning door transformation and wavelet in aspect of multivariate analysis, and concluded that the wavelet method is superior. However, both the vector and the wavelet methods need large amount of computation, thus requiring high-performance hardware to complete real-time data compression.

The purpose of this paper is to achieve effective and efficient utilization of sequential sensor signals by a new linear method of lossy data compression aim. As shown in Fig. 1, according to the signal type and the threshold value, the signal is filtered at the beginning of this method, then encapsulated and stored into a cache zone. When the cache zone is full, through comparing the maximum and minimum slopes, the encapsulated signal is compressed and finally archived into the historical data storage zone for later use. During the decompression process, the signal is reconstructed by linear interpolation of the data in the historical storage zone. This method is suitable for the compression and decompression of various types of sensor signals, especially for those containing massive data, multiple sampling, disturbance and redundancy.

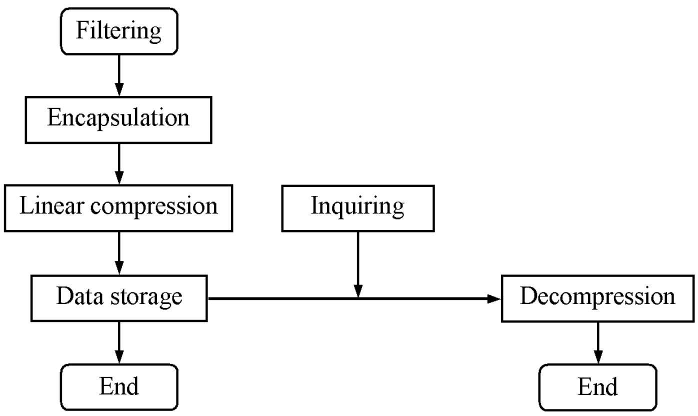

Fig. 1. Block diagram of the linear compression and decompression method proposed.

2. Linear Compression and Decompression

2.1. Preprocessing

The preprocessing of sensor signals includes the processes of filtering and encapsulation. Generally, the moving average algorithm is used to filter the signal. First of all, regard N sample values continuously obtained as a queue (the length of the queue is fixed as N), calculate the average value of this queue, put the new data sampled each time to the tail of the queue and at the same time get rid of the data at the original head of the queue. Then calculate the arithmetic average value of the N data in the queue and get the filtered result. For the signals from a system with relative large delays, use the weighted recursive average algorithm to filter the signal, which applies different weight on the data at different time. The weight is normally larger for the data closer to the current time. After filtering, encapsulate the data that satisfy the time interval of compression. The data encapsulated all contains the components of time scale, data value, data characteristics, etc.

2.2. Linear Compression

The compression process of the method proposed is divided into four steps.

Step1: For a group of data to be compressed (x_i, y_i) (i = 1, 2, …), establish a straight line based on the first data (x_1, y_1) and the second data (x_2, y_2) plus the baseline compression threshold value (0, t). The slope k_{max} of this straight line is regarded as the upper limit slope of the compression:

$$k_{max} = \frac{(y_2 + t - y_1)}{(x_2 - x_1)}, \tag{1}$$

where x represents time, y is the data value at time x, and t is the threshold value of the compression.

Establish a second straight line based on the subtraction of the first data (x_1, y_1) and the second data (x_2, y_2) from the compression threshold value (0, t). The slope k_{min} of this straight line is regarded as the lower limit slope of this compression:

$$k_{min} = \frac{(y_2 - t - y_1)}{(x_2 - x_1)}. \tag{2}$$

Step 2: Repeat step 1 using the first and third data, and get the new slopes:

$$k'_{max} = \frac{(y_3 + t - y_1)}{(x_3 - x_1)}, \tag{3}$$

$$k'_{min} = \frac{(y_3 - t - y_1)}{(x_3 - x_1)}. \tag{4}$$

Define

$$k_{max} = \min(k'_{max}, k_{max}), \tag{5}$$

$$k_{min} = \max(k'_{min}, k_{min}). \tag{6}$$

Step 3: Compare the current values of k_{max} and k_{min}. If k_{max} is greater than k_{min}, then $i = i + 1$ and return to step 2; if k_{max} is less than or equal to k_{min}, then the compression is terminated, document the current i as n, save the data (x_{n-1}, y_{n-1}) at the data point n–1 in the compression, and adjust the data value y_{n-1} at n–1 according to the average value of k_{max} and k_{min} at the data point n–1. We obtain:

$$y_{n-1} = \left(\frac{k_{\max} + k_{\min}}{2}\right) \cdot \left(x_{n-1} - x_1\right) + y_1 . \tag{7}$$

Save the refreshed data (x_{n-1}, y_{n-1}) to the historical data storage zone as shown in Fig. 2.

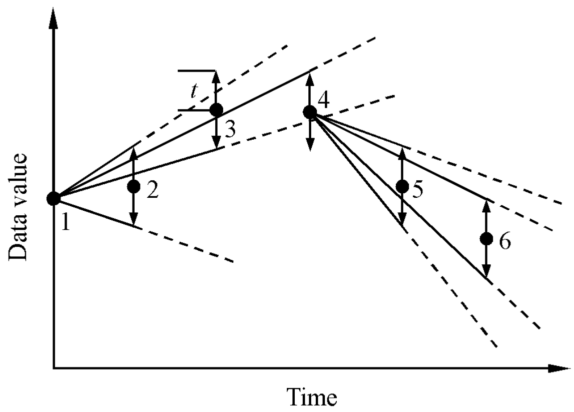

Fig. 2. Principle of linear compression process.

Step 4: Process the rest part of the data to be compressed till the last one. The specific procedure is: regard (x_n, y_n) at data point n as the first new data point, regard (x_{n+1}, y_{n+1}) at data point n+1 as the second new data point, repeat steps 1–3 till the last data, then the whole compression process is completed.

If the last data is reached during the compression, then save this data and terminate the compression. The linear compression process is shown in Fig. 3.

2.3. Decompression

During the decompression process, the data values at each time can be obtained through setting time step and linear interpolation according to the time step increment Δ_{inct}. The procedure of the decompression process is given in Fig. 4.

3. Compression Tests and Discussion

We use a standard sinusoidal signal and a measured dynamic pressure signal as original data to test the performance of the linear compression method proposed.

The standard sinusoidal signal contains totally 500 data points, and its period is 100 with amplitude of 10. Since the original data is a standard sinusoidal signal, it is not filtered herein. As seen in Fig. 5, when compression threshold values are set as 5 % and 1 %, the compression ratios by the linear compression method are 22.5:1 and 11.9:1. Note that the x-coordinate represents the data points, and the y-coordinate represents the data values.

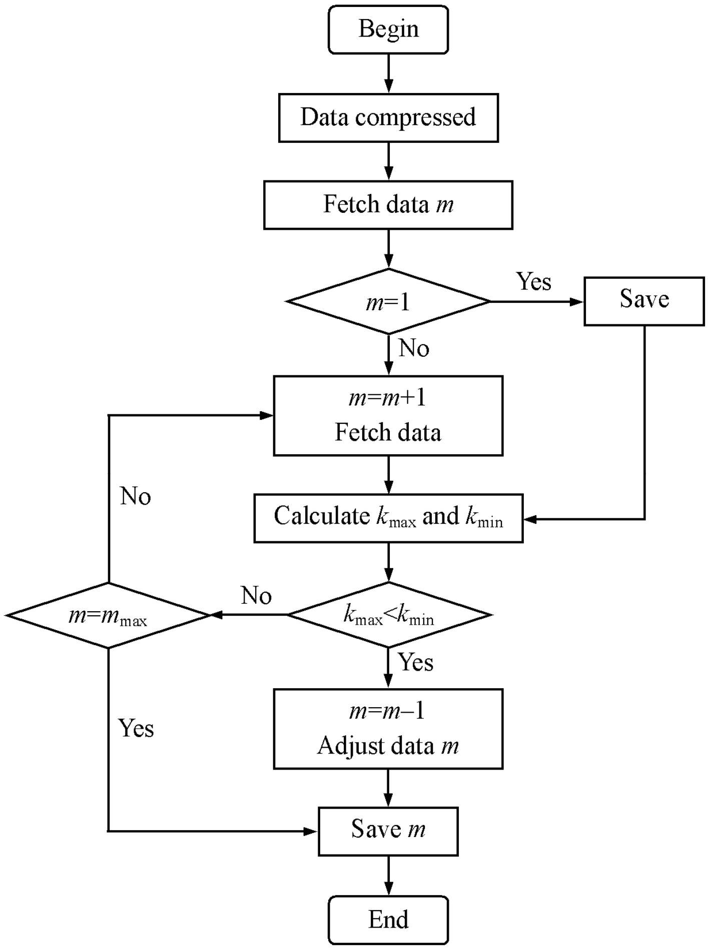

Fig. 3. Block diagram of linear compression process.

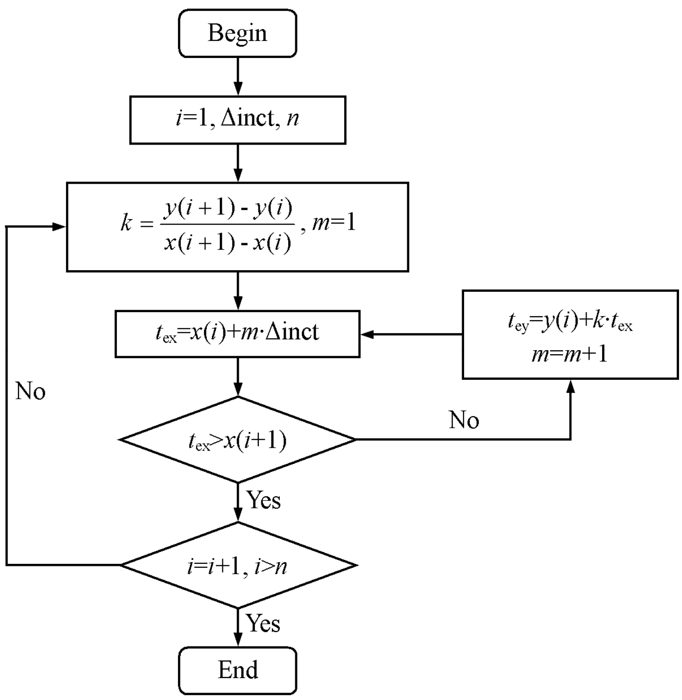

Fig. 4. Block diagram of decompression process.

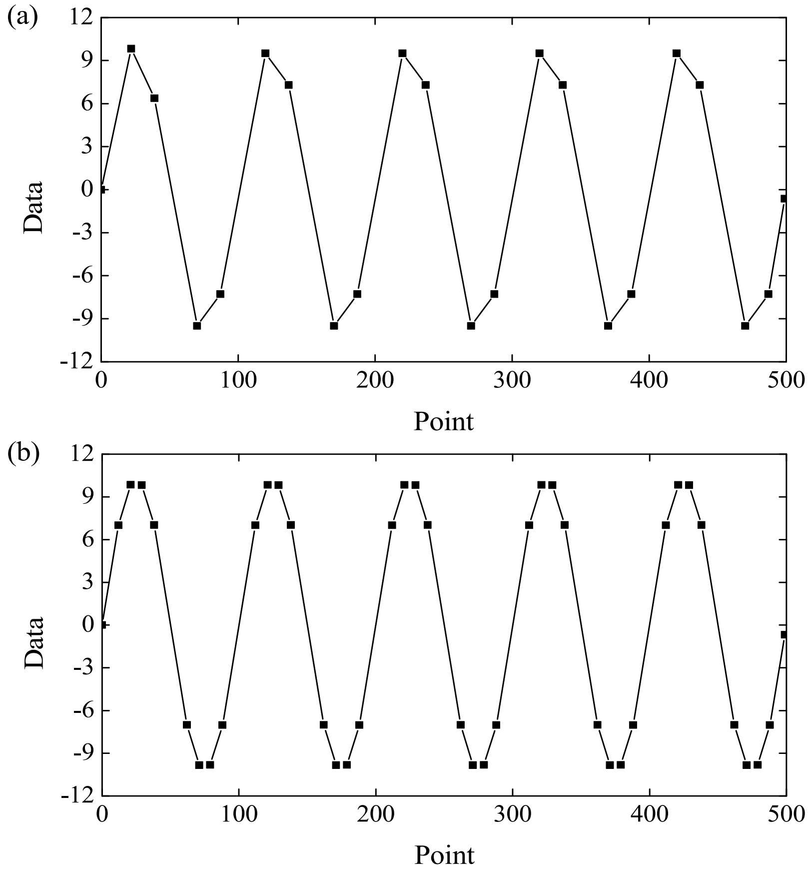

Fig. 5. Linear compression results of a standard sinusoidal signal: (a) Compression threshold value is 5%; (b) Compression threshold value is 1 %.

Fig. 6 gives the compression result of a standard sinusoidal signal by the spinning door transformation with a compression threshold value of 1%. Spinning door transformation is one of the most famous and efficient lossy compression algorithms in the field of process control. The spinning door transformation can only reach the compression ratio of 9.6:1. After decompression, compared with the original data, the average absolute error is 0.16 using the spinning door transformation; however, the average absolute error is 0.11 using the linear compression method proposed, which has a decrease of 31 %.

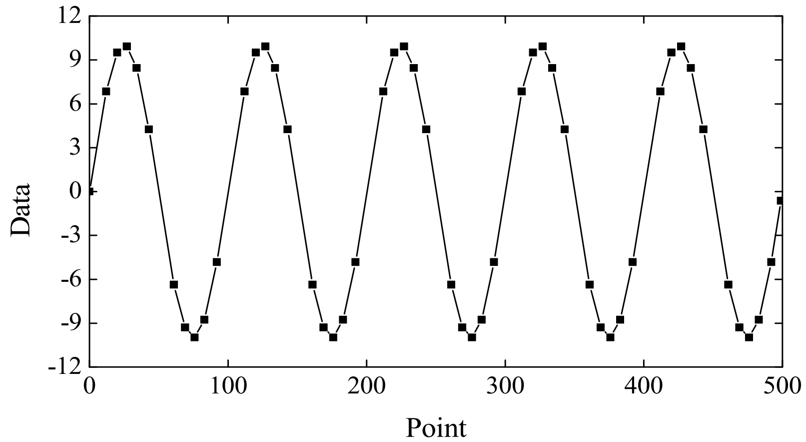

Fig. 6. Compression result of a standard sinusoidal signal using the spinning door transformation with compression threshold value of 1 %.

Fig. 7 shows the compression results of a measured dynamic pressure signal using the linear method and the spinning door transformation with a compression threshold value of 5 %. The measured dynamic pressure signal contains both low and high frequency components, and its sampling frequency is 1000 Hz with 2000 points. The results show that the linear method and the spinning door transformation have a compression ratio of 1.96:1 and 1.59:1, and after decompression their average absolute error are 0.12 and 0.21, respectively.

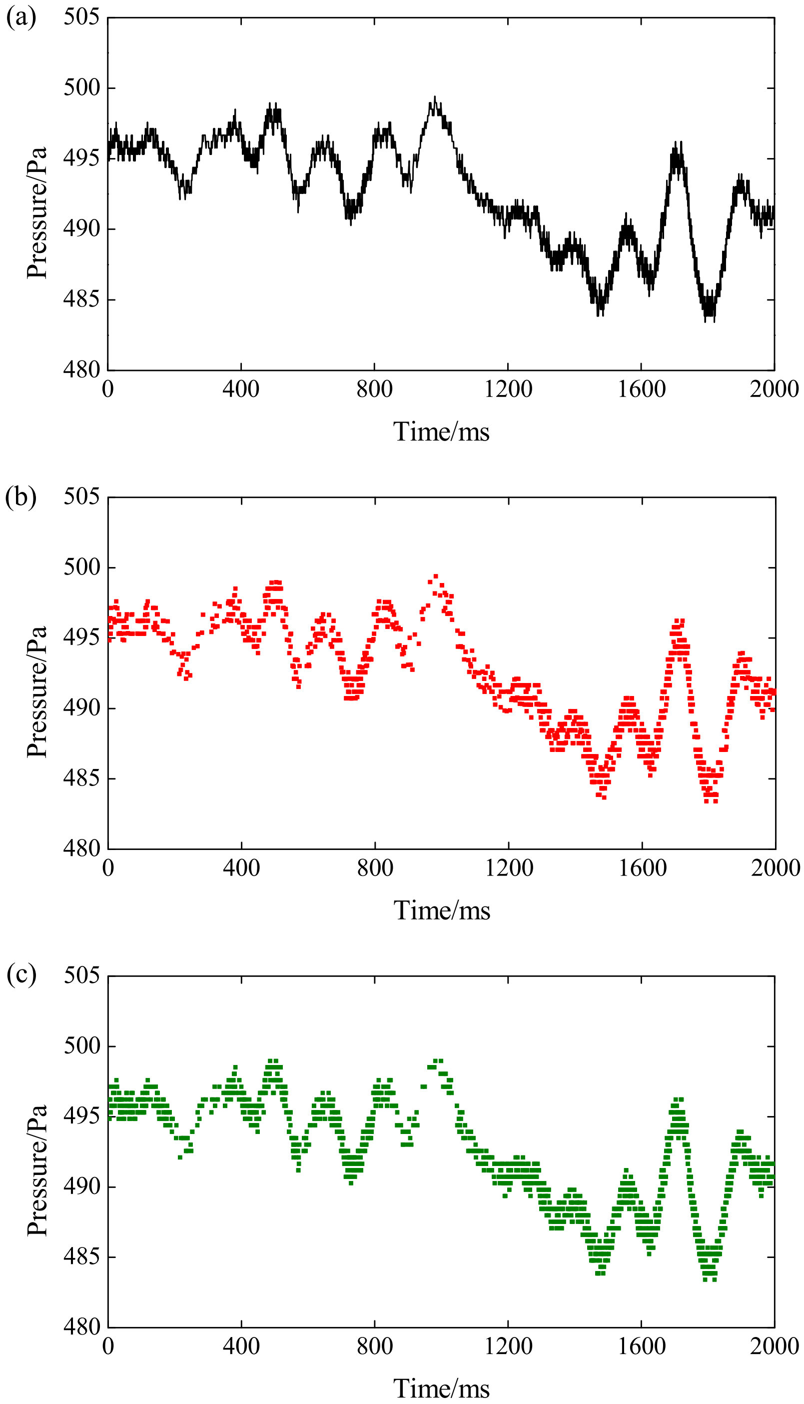

Fig. 7. Compression results of a dynamic pressure signal using linear method and spinning door transformation: (a) Original dynamic pressure signal; (b) Compression result of the linear compression; (c) Compression result of the spinning door transformation.

According to the results of the above two typical signals, it is seen that the linear compression method has better compression performance at both original data, it not only has higher compression ratio, but also it can keep the local characteristics of the original signal better.

4. Conclusions

This paper presents a new linear method of lossy data compression for effective and efficient utilization of sequential sensor signals. In the course of compression, the filtering and encapsulation are carried out first according to the signal type and the threshold value; second, the linear compression is conducted by comparing the maximum and minimum slopes of the sensor signal; third, the compressed signal is archived into the historical data storage zone for later use. Conversely, the signal is reconstructed by linear interpolation during the decompression process. According to the compression results of a standard sinusoidal signal and a measured dynamic pressure signal, it is found that compared with the spinning door transformation, this method has less compression error and higher compression ratio at the same compression threshold values, and moreover it can keep the local characteristics of the original signal better.

Acknowledgements

We are grateful for the financial support from the National Natural Science Foundation of China (Grant No. 51006125), and the Fundamental Research Funds for the Central Universities of China (Grant No. 2010QZZD0107).

References

[1]. S. Y. Yurish, Multichannel data acquisition system for smart sensor and transducers, *Sensors & Transducers,* Vol. 8, Issue 2, 2010, pp. 1-12.
[2]. P. Singh, R. D. S. Yadava, A fusion approach to feature extraction by wavelet decomposition and principal component analysis in transient signal processing of SAW odor sensor array, *Sensors & Transducers*, Vol. 126, Issue 3, 2011, pp. 64-73.
[3]. P. A Langen, The use of historical data storage and retrieval systems at nuclear power plants, *IEEE Transactions on Nuclear Science*, Vol. 31, Issue 1, 1984, pp. 844-848.
[4]. J. C Hale, H. L. Sellas, Historical data recording for process computers, *Chemical Engineering Progress*, Vol. 77, Issue 11, 1981, pp. 38-43.
[5]. R. S. H. Mah, A. C. Tamhanea, S. H. Tunga, et al., Process trending with piecewise linear smoothing, *Computers and Chemical Engineering*, Vol. 19, Issue 2, 1995, pp. 129-137.
[6]. R. M. Gray, Vector quantization, *IEEE ASSP Magazine*, Vol. 1, Issue 2, 1984, pp. 4-29.
[7]. J. F. MacGregor, T. Kourti, Statistical process control of multivariate process, *Control Engineering Practice*, Vol. 3, Issue 3, 1995, pp. 403-414.
[8]. B. R. Bakshi, G. Stephanopoulos, Representation of process trends III: multi-scale extraction of trends from process data, *Computers and Chemical Engineering*, Vol. 18, Issue 4, 1994, pp. 267-302.
[9]. B. R. Bakshi, G. Stephanopoulos, Representation of process trends IV: induction of real-time patterns from operating data for diagnosis and supervisory control, *Computers and Chemical Engineering*, Vol. 18, Issue 4, 1994, pp. 303-332.
[10]. B. R. Bakshi, G. Stephanopoulos, Compression of chemical process data by functional approximation and feature extraction, *AIChE Journal*, Vol. 42, Issue 2, 1996, pp. 477-492.
[11]. A. Singhal, D. Seborg, Effect of data compression on pattern matching in historical data, *Industrial & Engineering Chemistry Research*, Vol. 44, Issue 9, 2005, pp. 3203–3212.
[12]. S. A. Imtiaz, M. Choudhury, S. L. Shah, Building multivariate models from compressed data, *Industrial & Engineering Chemistry Research*, Vol. 46, Issue 2, 2007, pp. 481-491.

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 additional, 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/Submition.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