International Journal of Modern Electronics and Communication Engineering (IJMECE) ISSN: 2321-2152
Volume No.-7, Issue No.-2, March, 2019

Influences of Data Compression Method in Wireless Sensor Networks

Rajiv Ranjan Tewari
Department of Electronics and Communication
J.K. Institute of Applied Physics And Technology
University of Allahabad, Allahabad, India
E-mail: tewari.rr@redi mail.com

Snehi Saraswati
Department of Electronics and Communication
J.K. Institute of Applied Physics And Technology
University of Allahabad, Allahabad, India
E-mail: snehisaraswati@gmail.com

Abstract: In WSNs, the conservation of energy is a very important factor. The energy is consumed during radio communication. The sensor lifetime is extended by reducing the transmission overhead. Here, a data compression technique has been proposed. This technique is applied in temporal correlation of sensing data, transformation of data from one dimension to two dimension and data separation having 16 bits in upper and lower each 2- dimensional using discrete Fourier transform method. It is observed that proposed technique is helpful in reducing the consumption of energy and it may be obtainable by data rate control.

Keywords: Wireless Sensor Networks, Two-dimensional Discrete Fourier Transform, Wavelet based compression, Root-mean-square error, Compression Ratio.

I. INTRODUCTION

In the study of WSNs, there are important roles of the relief of natural disaster, military target tracking, exploration of dangerous environment and seismal. A base station, sensor nodes consists of embedded processors and radio transceiver of low power are main components of WSNs. Sensor nodes are applied to sense, measure and collect the required informations from the environment or local decision process. Sensor nodes transmit the sensing data to the sink for fulfilment of need of users query or local decision process. Sensor node communicate with each other and also with base station using their wireless radios.

A radio is used in the form of wireless communication which transforms the data to the base station(or sink) because there are limited memory in sensor nodes and they are located in difficult-to-access locations. The power consumption is the main factor in WSNs. There is limited and insufficient techniques to reduce energy consumption in communication. Thus, the energy efficiency is in one of the core issues to be solved in WSNs.

The energy is consumed during the process of communication between sensor nodes. Thus, during the process of achieving the necessary required network operation, there is a need of minimizing the communication overhead. There are mainly two categories of energy conservation during communication:

1. Duty-cycling Methods
2. Data-driven methods

The duty-cycling methods are concerned with topology (cartography) control and the management of power. Data reduction and energy-efficient data accession are main components of data-driven methods. The aim of this paper is to develop a data compression technique to decrease the amount of data to be distributed to the base station (or sink) with consumption of minimum energy.

II. OBJECTIVES OF THIS RESEARCH PAPER

The objectives of this research paper are given below :

1. There are needs of Wireless Sensor Networks which are comfortable for real time monitoring of datas having a high resolution (i.e. 15 bit to 35 bit) and sampling rate (i.e. 45kHz 1.5MHz). The sound pressure, vibration and strain of sensing data are expressed in the numerical value. In case of event detected by sensor nodes, the datas should be transmitted to the sink instantly by sensor nodes. The overhead of communication is the main factor of the consumption of energy.

2. Some degree of correlation is obtained by sensing data. Generally a high temporal correlation is presented by sensing data when it is collected by a single node. The physical phenomenon presents the type of close relationship along the axis of time at a particular time. If the time interval between two time points increases then the level of correlation between them decreases. Thus, the data is collected by sensor nodes includes huge or redundant informations related to WSNs.

In order to save the energy, the some redundant informations can be removed by utilizing the structural correlation among observed data by sensors. This effects in transmitting less data. Ahmed et.al[[1]] discussed the correlated data and uncorrelated coefficients using Discrete Fourier Transform (DFT) technique. Bai.et.al[[3]] and Wang et.al[[8]] studied the techniques of data reduction using DCT related to aggregation data.
In this research paper, an attempt has been explored following two new ideas concerned for reduction of transmission of related sensing data.

International Journal of Modern Electronics and Communication Engineering (IJMECE) ISSN: 2321-2152
Volume No.-7, Issue No.-2, March, 2019

(i) The transformation of temporal correlation to structual correlation in one sensing data is possible.
(ii) In numerical data having high resolution, the compression and transmission of the sensing data are more effective and efficient after separating into following two parts:
(a) upper bit part
and (b) lower bit part.

For the sake of first idea, sensing data of one dimension is transferred to data of two dimension to reduce the extra information of measurand. More clearly, the spatial correlation is exploited instead of temporal correlation.

For second idea, the quantized value expressed to binary numerical is exploited and it is transformed to the format of decimal number as scaling factor. It is remarkable to note that one of the two parts is more important after examining the useful related component of the sensing data.

The aim of the research paper is to reduce the consumption of power of sensor nodes by the technique of data compression in WSNs. This technique is consisted of following three steps:

a. One dimensional sensing data is taken in a group of 16x16 blocks and transformed to 2-D data.
b. The data of 2- dimention is separated into following two parts:
(i) upper part
and (ii) lower part.
c. Using 2D-DFT each divided part is compressed. This method is applicable to data rate control.

III. EXPECTED CHARACTERISTICS OF PROPOSED SENSING DATA

An environment is considered. At this environment, a huge amount of data is generally generated in a very short interval. As far as real time monitoring is considered, the user do not need to send all these informations of sensor nodes. Thus minor extra information may be neglected and consequently these cannot be sent to the concerned sink. Thus, there is a compromise between accuracy and compression ratio of concerned transmitted data.
Fig. 1 shows that the original data is same as upper 16 bit data. The lower 16 bit information is less important than the upper 16 bit information. The different compression ratios may be adapted to the lower and upper parts. Hence, the divided parts is transmitted with different compression ratio as per requirement. Here, part having useful information is considered having accuracy over the ratio of compression.

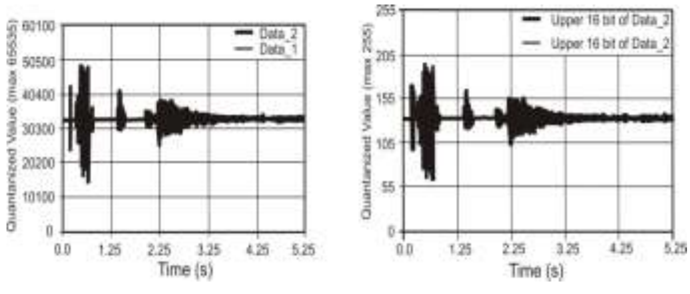


Figure 1: (a) Sample data with 32 bit resolution
(b) Sample data with upper 16 bit

Several techniques are known to facilitate the issue of limited power by the help of reducing the amount of data. These are applied in different fields of communication. Some of them have been also applied in WSNs.
In WSNs, data aggregation is applied in reducing the cost of message by reducing similar sensing data into some specific values. The importance of in-network processing method is measured by its applications. Anastasi et.al[[2]] and Fasolo et.at[[4]] have already studied the energy conservation and in-network aggregation techniques.
The amount of information set by source nodes can be reduced by techniques of data compression. There is a need of encoding information at data generating nodes and decoding at the sink. Pradhan et.al[[6]] and Tang et al[[7]] have discussed compression techniques and syndromes source coding. The compression techniques can be applied in other fields also other than WSNs. JPEG 200 (Wavelet based compression) is designed mainly for image compression.According to Ganesan et. al[[5]], it works as per steps given below:
(i) At first, it divides the concerned image into numbers of small pixels
and then (ii) compresses images by wavelet transform technique and quantization. The DWT is helpful in generating structural-temporal compression of sensing data in each level.
Data prediction is concerned with the building of an abstraction of a sensed situation. The model indicates the value which is sensed by sensor nodes having some error bounds. This resides at both of the sensors and the sink. If the desired accuracy is achieved then queries (issued by concerned users) may be examined at the sink through the model.There is no need to obtain the exact data from nodes. If the model is not up to the mark then the denotative communication between sensor nodes and the sink is required. In this case, the actual sample has to be repaired and consequently the model should be updated. Thus, the prediction of data reduces the quantity of information/message sent by source nodes and the energy consumption during the process of communication.
It is a matter of great concerned for research point of view that our adaptive sampling should reduce the number of samples during exploiting spatio-temporal correlations between data. The required data can change slowly with time.The number of acquisitions may be reduced by temporal correlations.This approach is helpful when the required phenomenon is unable to change between areas covered by neighbouring nodes. Due to advantage from spatial correlations among sensing data, energy during sampling can be reduced. Hence, temporal and spatial correlations can reduce the amount of data which is to be obtained.

IV. PROPOSED COMPRESSION TECHNIQUES

Our main aim of this research paper is to reduce the power consumption of sensor nodes using the technique of data compression. A technique based on correlation method has been proposed. It is composed of three phases.
The operation steps of this scheme are given below:
(i) The data dimension transformation, (ii) Separation of Data (iii) FDT (iv) Quantization (v) Entropy encoding (vi) Frame rebuild (vii) Transmission of data

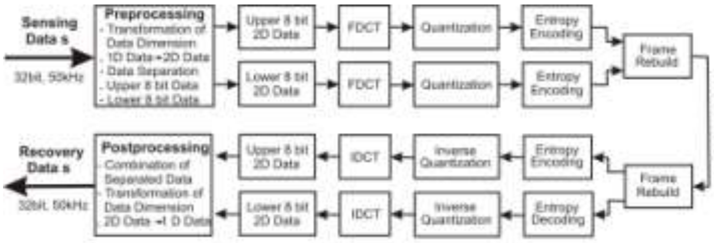


Figure 2: Procedure of data compression and decompression

The quantized value is to be exploited. This is expressed by binary numeral and then it is transformed in the form of decimal number as scaling factor. In this way, the value of sensing data is quantized.

{d1, d2, d3 ... d255, d256}

d1	⋯	d8	d65	⋯	d72
d9	⋯	⋮	d73	⋯	⋮
⋮	⋯	⋮	⋮	⋯	⋮
d57	⋯	d64	d121	⋯	d128
d129	⋯	d136	d193	⋯	d200
d137	⋯		d201	⋯	⋮
⋮	⋯		⋮	⋯	⋮
d185	⋯	d192	d249	⋯	d256

{d1, d2, d3 ... d255, d256}

d1	d2	⋯	⋯	⋯	d15	d16
d17	⋯	⋯	⋯	⋯	d31	d32
⋮	⋯	⋯	⋯	⋯	⋯	⋮
⋮	⋯	⋯	⋯	⋯	⋯	⋮
⋮	⋯	⋯	⋯	⋯	⋯	⋮
⋮	⋯	⋯	⋯	⋯	⋯	⋮
d233	⋯	⋯	⋯	⋯	⋯	d240
d241	⋯	⋯	⋯	⋯	⋯	d256

(a)Tranformation after grouped into 16x16 (b)Tranformation in sequence

Figure 3: Examples of Data Transformation

IV (i). Steps of Pre-processing

The Structural correlation is exploited in place of temporal correlation. In one sensing data, the temporal correlation of sensing data is generally transformed to structural correlation. A group of 16x16 blocks is developed for one dimensional sensing data.It is transformed to 2-Dimenssional data which is shown in fig 3(a). As far as separation is concerned, 2-Dimenssional data has been divided into upper and lower 16 bit data

IV (ii).Discrete Fourier Transform Technique and compression of data

The two-dimensional discrete Fourier Transform (2D-DFT) is applied on upper and lower 16 bit data. DCT and DST (discrete sine transforms) are particular case of discrete Fourier Transform. DFT is used in the area of signal processing. 2D-DFT is applied in image processing. A signal of spatial domain is transformed to frequency domain and extracted significant values of the concerned image. DFT is used to transfer the correlation spatial data to coefficients of uncorrelated frequency. In our case, the major part of energy to concerned physical phenomenon is considered on the parts of lower frequencies. In proposed technique, the lower frequency coefficients are transmitted to the sink. During this process, the loss consumption of energy is observed.It is remarkable to note that during the process of transmission, there is a few loss of information in comparison of original data. Thus, this technique is very useful in comparison of data. Forward Discrete Fourier Transform is give in eqn(1) works as an analyzer of harmonic phenomena and Inverse Discrete Fourier Transform given in eqn(2) acts as a harmonic synthesizer.

2-D Discrete Fourier Transform is defined by,

$$F(u,v)=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}f(x,y)e^{i((2x+1)\frac{u\pi}{32}+(2y+1)\frac{v\pi}{32})}$$

$$=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}f(x,y)\left[\cos(2x+1)\frac{u\pi}{32}+i\sin(2x+1)\frac{u\pi}{32}\right]$$

$$\times\left[\cos(2y+1)\frac{v\pi}{32}+i\sin(2y+1)\frac{v\pi}{32}\right]$$

$$=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\cos(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

$$+\frac{1}{4}C(u)C(v)i\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\cos(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right]$$

$$+\frac{1}{4}C(u)C(v)i\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\sin(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

$$+\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\sin(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right]$$

(4.1)

Then,

2-D Discrete Fourier Cosine Transform F_c is

$$F_c=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\cos(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

(4.2)

$$F_{cs}=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\cos(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right]$$

(4.3)

$$F_{sc}=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\sin(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

(4.4)

$$F_s=\frac{1}{4}C(u)C(v)\sum_{x=0}^{15}\sum_{y=0}^{15}\left[f(x,y)\sin(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right]$$

(4.5)

2-D Inverse Discrete Fourier Transform is defined by,

$$f(x,y)=\frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15}C(u)C(v)F(u,v)e^{-i((2x+1)\frac{u\pi}{32}+(2y+1)\frac{v\pi}{32})}$$

$$=\frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15}C(u)C(v)F(u,v)\left[\cos(2x+1)\frac{u\pi}{32}-i\sin(2x+1)\frac{u\pi}{32}\right]$$

International Journal of Modern Electronics and Communication Engineering (IJMECE) ISSN: 2321-2152
Volume No.-7, Issue No.-2, March, 2019

$$\times\left[\cos(2y+1)\frac{v\pi}{32} - i\sin(2y+1)\frac{v\pi}{32}\right]$$

$$= \frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F(u,v)\cos(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

$$-\frac{1}{4}i\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F(u,v)\cos(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right]$$

$$-\frac{1}{4}i\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F(u,v)\sin(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right]$$

$$+\frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F(u,v)\sin(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right] \quad (4.6)$$

Then,

2-D Inverse Discrete Fourier Cosine Transform is

$$f(x,y) = \frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F_c(u,v)\cos(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right] \quad (4.7)$$

2-D Inverse Discrete Fourier cosine-sine Transform is

$$f(x,y) = \frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F_{cs}(u,v)\cos(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right] \quad (4.8)$$

2-D Inverse Discrete Fourier sine-cosine Transform is

$$f(x,y) = \frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F_{sc}(u,v)\sin(2x+1)\frac{u\pi}{32}\ \cos(2y+1)\frac{v\pi}{32}\right] \quad (4.9)$$

2-D Inverse Discrete Fourier sine Transform is

$$f(x,y) = \frac{1}{4}\sum_{u=0}^{15}\sum_{v=0}^{15} C(u)C(v)\left[F_s(u,v)\sin(2x+1)\frac{u\pi}{32}\ \sin(2y+1)\frac{v\pi}{32}\right] \quad (4.10)$$

Generally the table of quantization is well known to the user and concerned sensor nodes. After output from the forward discrete Fourier transform, each of DCT coefficient is uniformly quantized using a table of quantization . By the help of this table the compression ratio having upper as well as lower 16 bit data can be controlled. Hence the divided parts of data having required compression ratio are transmitted.

The entropy coding is considered for the final encoder processing step using D.C.T. There is role of statistical characteristics of quantized coefficients in their encoding. The steps of encoding achieve additional compression. In this process, Huffman coding is helpful in entropy coding. One or more sets of Huffman code tables may be specified by view of applications in Huffman coding. The tables for compressing an image are required to decompress it.

It is remarkable to note that the compressed upper as well as lower 16 bit data is taken together for the sake of transmission to the sink in frame rebuild step.

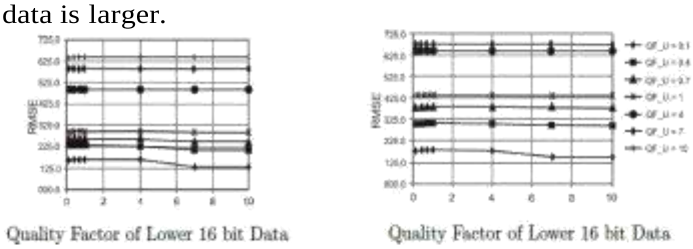
V. SIMULATION RESULTS

The efficiency of the proposed compression techniques has been evaluated. Two samples have been obtained by real sensor. By changing the quality factor of quantization table having upper 16 bit and lower 16 bit in correlation level compression ratio and root-mean-square error (RMSE) have been explored. The data representation size obtained by a data compression algorithm is reduced by quantifying it with the help of data compression ratio. The ratio of the compressed size and uncompressed size of the data is the data compression ratio. It is generally used in measuring the physical compression of the data. The differences between original sensing values and recovery values have been measured by RMSE (i.e Root-mean-square error).

In Fig (4), the RMSE value of grouped transformed data and sequential transformed data have been exemplified. It is observed that whenever Q.F. (the quality factor) of the upper 16 bit data is low, RMSE value is low without influenced by Q.F. of lower 16 bit data. RMSE of the sequential transformed data is more than the grouped transformed data.

In Fig(5), the performance of compression of grouped transformed data has been observed better than that of the sequential transformed data.

Fig(6) shows the exploitation of coefficient of correlation (r) having range between -1 and 1. When r is closer to +1 or -1, the two variables are closely related to each other. If there is no relation between the variables, the r is close to 0. If the correlation coefficient is smaller the Q.F. of upper 16 bit data is larger.



(a)Grouped Transformed Data (b)Sequential Transformed Data

Figure 4: RMSE of Recovery Data

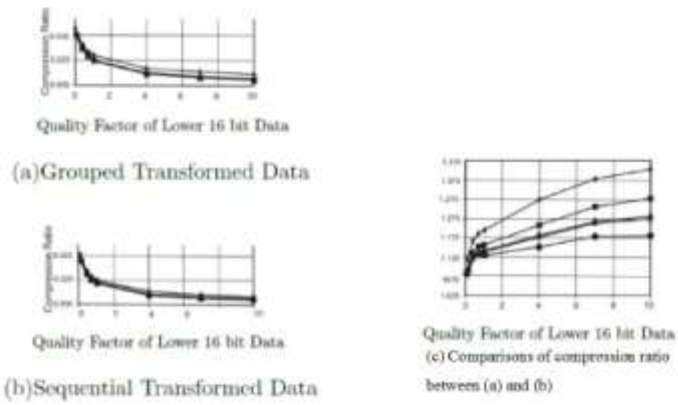
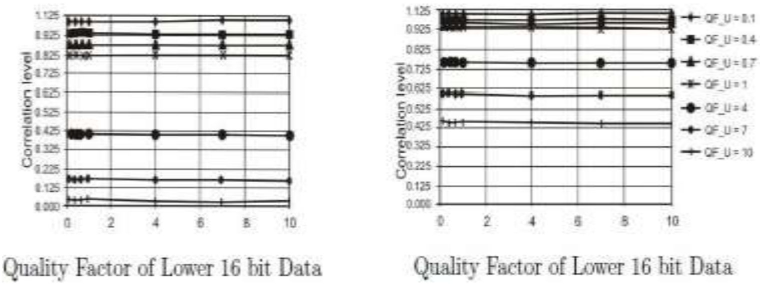


Figure 5: Compression Ratio of grouped and sequential transformed data

International Journal of Modern Electronics and Communication Engineering (IJMECE) ISSN: 2321-2152
Volume No.-7, Issue No.-2, March, 2019



(a) Grouped Transformed Data (b) Sequential Transformed Data

Figure 6: Correlation coefficient of grouped and sequential transformed data

VI. CONCLUSIONS

In this paper following conclusions have been derived by considering the efficiency of proposed data compressing techniques:

1. The proposed data compression technique reduces the communication overhead in wireless sensor networks (WSNs).
2. During communication under proposed data compression technique the limited energy is saved.
3. The specific characteristics of the sensing data is applied for better communication with temporal correlation.
4. By the process of simulation, the temporal correlation may be transformed to spatial correlation.
5. Discrete Cosine Transformed (DCT) is used as a technique to analyse and to decorrelate the sensing data.
6. DSST (Discrete sine-sine Transform), DCST (Discrete cosine-sine Transform) can be applied for the detailed study of sensing data.
7. It is important to note that results observed by DCT, DSCT, DCST, DSST are almost same.
8. Quantization Table has been taken in account for achieving the data compression.
9. The compression ratio is minimized by quality factor (Q.F.). Thus, the proposed technique is generally helped to data rate control.
10. In case of numerical sensing data, the proposed technique is more effective in compression as well as transmission of sensing data as per our requirement. The above mentioned conclusions are the significant achievements of the proposed data compression technique in WSNs.

ACKNOWLEDGMENT

Authors are grateful to the referee for his valuable comments and suggestions which improve the presentation of this research paper.

REFERENCES

[1] Ahmed, N., Natarajan, T. and Rao, K.R., 1974. Discrete cosine transform. IEEE transactions on Computers, 100(1), pp.90-93.

[2] Anastasi, G., Conti, M., Di Francesco, M. and Passarella, A., 2009. Energy conservation in wireless sensor networks: A survey. Ad hoc networks, 7(3), pp.537-568.

[3] Bai, F. and Jamalipour, A., 2008, May. 3D-DCT data aggregation technique for regularly deployed wireless sensor networks. In Communications, 2008. ICC'08. IEEE International Conference on (pp. 2102-2106). IEEE.

[4] Fasolo, E., Rossi, M., Widmer, J. and Zorzi, M., 2007. In-network aggregation techniques for wireless sensor networks: a survey. IEEE Wireless Communications, 14(2).

[5] Ganesan, D., Greenstein, B., Estrin, D., Heidemann, J. and Govindan, R., 2005. Multiresolution storage and search in sensor networks. ACM Transactions on Storage (TOS), 1(3), pp.277-315.

[6] Pradhan, S.S. and Ramchandran, K., 2003. Distributed source coding using syndromes (DISCUS): Design and construction. IEEE transactions on information theory, 49(3), pp.626-643.

[7] Tang, C. and Raghavendra, C.S., 2004. Compression techniques for wireless sensor networks. In Wireless sensor networks (pp. 207-231). Springer, Boston, MA.

[8] Wang, Y.C., Hsieh, Y.Y. and Tseng, Y.C., 2009. Multiresolution spatial and temporal coding in a wireless sensor network for long-term monitoring applications. IEEE Transactions on Computers, 58(6), pp.827-838.