

July 2012

Intelligent Image compression in Multi-agent system

Jibanananda Mishra

DRIEMS, CUTTACK, jeevan_mishra2000@yahoo.co.in

Bishnu Prasad Mishra

DRIEMS - Cuttack, SIT - Bhubaneswar, CET – Bhubaneswar, India, Bishnu_prasad@rediffmail.com

Rabinarayana Parida

SIT, BBSR, BPUT, rabiparida@rediffmail.com

Ranjan Kumar Jena

CET, BBSR, BPUT, ranjankjena@gmail.com

Follow this and additional works at: <https://www.interscience.in/ijcsi>



Part of the [Computer Engineering Commons](#), [Information Security Commons](#), and the [Systems and Communications Commons](#)

Recommended Citation

Mishra, Jibanananda; Mishra, Bishnu Prasad; Parida, Rabinarayana; and Jena, Ranjan Kumar (2012) "Intelligent Image compression in Multi-agent system," *International Journal of Computer Science and Informatics*: Vol. 2 : Iss. 1 , Article 2.

DOI: 10.47893/IJCSI.2012.1058

Available at: <https://www.interscience.in/ijcsi/vol2/iss1/2>

This Article is brought to you for free and open access by the Interscience Journals at Interscience Research Network. It has been accepted for inclusion in International Journal of Computer Science and Informatics by an authorized editor of Interscience Research Network. For more information, please contact sritampatnaik@gmail.com.

Intelligent Image compression in Multi-agent system

Jibanananda Mishra , Bishnu Prasad Mishra , Rabinarayana Parida , Ranjan Kumar Jena

DRIEMS - Cuttack , SIT - Bhubaneswar , CET – Bhubaneswar , India

E-mail : Jeevan_mishra2000@yahoo.co.in , Bishnu_prasad@rediffmail.com, rabiparida@rediffmail.com,

ranjankjena@gmail.com

Abstract: - When using wireless sensor networks for real-time data transmission, some critical points should be considered. Restricted computational power, memory limitations, narrow bandwidth and energy supplied present strong limits in sensor nodes. Therefore, maximizing network lifetime and minimizing energy consumption are always optimization goals. To reduce the energy consumption of the sensor network during image transmission, an energy efficient image compression scheme is proposed. The image compression scheme reduces the required memory. To address the above mentioned concerns, in this paper we describe an approach of image transmission in WSNs , taking advantage of JPEG2000 still image compression standard and using MATLAB . These features were achieved using techniques: the Discrete Wavelet Transform (DWT), and Embedded Block Coding with Optimized Truncation (EBCOT). Performance of the proposed image compression scheme is investigated with respect to image quality and energy consumption. Simulation results are presented and show that the proposed scheme optimizes network lifetime and reduces significantly the amount of required memory by analyzing the functional influence of each parameter of this distributed image compression algorithm.

Keywords: WSN, Image compression, Energy conservation, System lifetime, JPEG2000, Mat lab

I. INTRODUCTION

Image transmission optimization through WSNs is mainly done by the implementation of distributed image compression algorithm embedded in order to

reduce the number of transmitted bits, thus reducing the energy consumption. The use of distributed image compression in resource-constrained networks is essential. Even if the necessary total energy for the whole system is increased, the energy needed for every node is reduced, which prolongs the network lifetime. This technique is based on the fact that an individual node does not have sufficient computational power to completely compress a large volume of data to meet the application requirements; this is not possible unless the node distributes the computational task among other nodes. In this case, a distributed method to share the processing task is necessary.

In this paper, we propose an alternative image transmission approach in WSNs, based on JPEG2000 image compression standard. JPEG2000 can provide various new additional functions such as high resolutions image compression, progressive transmission and scalable image coding. This approach is based on discrete wavelet transform (DWT) and Embedded Block Coding with Optimized Truncation (EBCOT) which uses a better order of transmission. This paper is organized as follows: Section II describes general architecture of a wireless sensor node. Image transmission to WSN is proposed in section III. Experimental results are shown in Section IV. Finally, section V concludes this work.

II. GENERAL ARCHITECTURE OF A WIRELESS SENSOR NODE

Fig. 1 shows the architecture of a typical wireless sensor node, as usually assumed in the literature. It consists of four main components: (i) a

sensing unit including one or more sensors and an analog-to-digital converters for data acquisition; (ii) a processing unit including a micro-controller and memory for local data processing; (iii) a radio subsystem for wireless data communication (RF unit); and (iv) a power supply unit. Depending on the specific application, sensor nodes may also include additional components which are optional such as a location finding system to determine their position, a mobilizer to change their location or configuration.

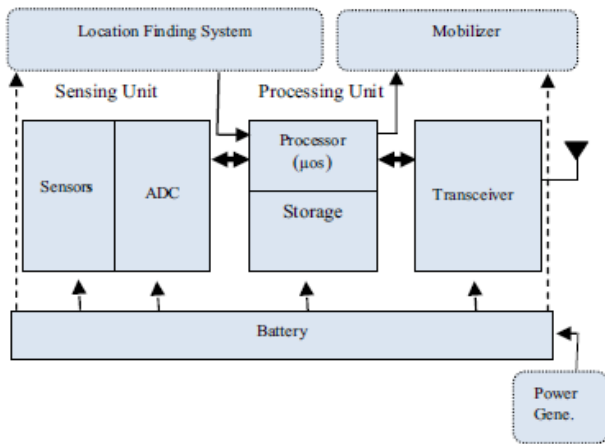


Fig. 1 Architecture of a typical wireless sensor node.

For wireless multimedia network, sensor nodes are equipped with multimedia devices such as cameras. These devices are smaller, and offer more performances in terms of speed and image quality. Thus such network will have the capability to transmit multimedia data. The most important requirements of image transmission in WSNs are: Image sensing, allocated memory and image processing.

III.1 IMAGE PROCESSING IN WSNs

As the radio subsystem is one of the most power consuming parts in sensors node, it is obvious that

reducing transmitted data will save energy. However, the most evident solution is the image compression. The purpose of image compression is to reduce the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible. In this paper, the proposed image transmission scheme is based on wavelet image transform. The structure of a transform coder is illustrated in Fig. 2:

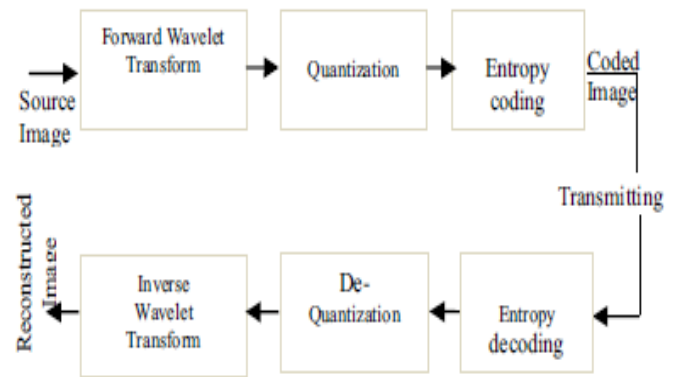


Fig. 2 Functional block diagram of JPEG 2000 encoder

The main objectives achieved by this image compressing system are: Progressive transmission, progressive quality, reduced allocated memory, minimized energy consumption, and optimized network lifetime. More recently, the wavelet transform has gained widespread acceptance in signal processing in general and in image compression research in particular. Wavelet-based coding (also referred to as lifting scheme (LS)) is more robust under transmission and decoding errors, and also facilitates progressive transmission of images. Wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Theoretically, DWT is a 2 dimensional separable filtering operation across rows and columns of input image. The DWT based on the

concept of multi-resolutions which facilitates progressive transmission of images. This is achieved by first applying the low-pass filter L and a high-pass filter H to the lines of samples, row-by- row, and then re-filtering the output to the columns by the same filters. As a result, the image is divided into 4 sub bands: low-low (LL_1), low-high (LH_1), high-low (HL_1) and high-high (HH_1) [5]. The high-pass sub-band represents residual information of the original image, needed for the perfect reconstruction of the original set from the lower solution version. Specifically, the LL_1 sub-band can be transformed again to form LL_2 , LH_2 , HL_2 , and HH_2 sub-bands, producing a two-level wavelet transform and so on.

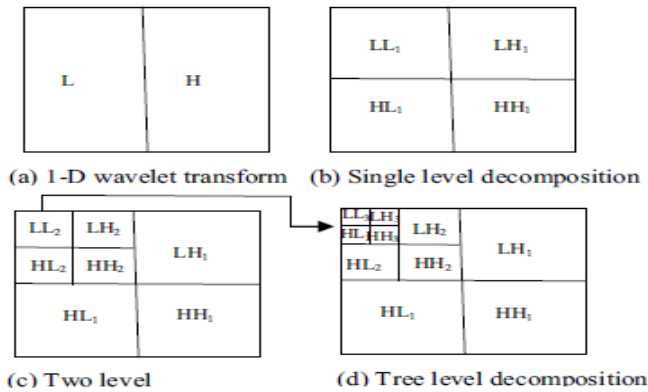


Fig.3. Illustration of wavelet spectral decomposition

After the DWT, all the sub-bands are quantized to reduce the precision of the sub-bands and contribute in achieving compression. The quantized DWT coefficients are converted into sign-magnitude represented prior to entropy coding. In the Embedded Block Coding method which is used in JPEG2000 standard, each sub-band (corresponding to LL, LH, HL and HH component at each wavelet decomposition level) is divided into small blocks called ‘code blocks’. And then each code block is

coded independently from the other ones thus producing an elementary embedded bit-stream. During the coding phase, each code-block is decomposed into a number of bit-planes: One sign bit-plane and several magnitude bit-planes. The entropy coder for JPEG-2000 uses embedded block coding with optimal truncation (EBCOT). EBCOT is divided into two coding pass: Significance Propagation Pass (Pass1), Magnitude Refinement Pass (pass2) and Cleanup Pass (pass3); the tier-2 is to organize the portfolio among bit-streams from every block [8].

III.2. DISTRIBUTED TASK OF IMAGE COMPRESSION

The basic idea of the proposed distributed image compression is distributing the workload of task to several groups of nodes along the path from the source to the sink. The key issue in the design of distributed task of image compression is data exchange. In this proposition, data is broadcasted to all processors to speed up the execution time which may optimize network lifetime and increase the energy consumption. An example of distributed cluster- based compression using four nodes in each cluster is shown in Fig. 4.

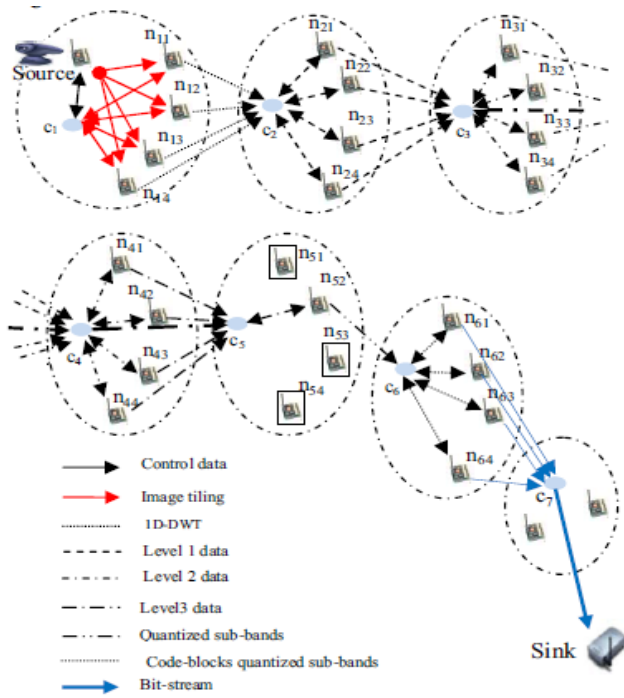
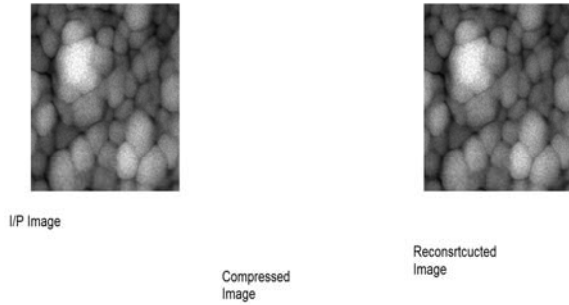


Fig. 4 . Data exchange of distributed task for image compression in a multi-hop wireless network. Three levels of wavelet decomposition are used.

Where applying the scenario proposed in III and after receiving a query from a source node s , the cluster head c_1 selects a set of nodes n_{1i} ($i = 1 \dots 4$) in the cluster which will take part in the distributed tasks then informs source node, the first stage concerns the data partitioning scheme is parallel wavelet transform. The source divides the original image into tile and transmits them to n_{1i} (n_{11} , n_{12} , n_{13} and n_{14}). Those nodes run 1D-DWT (horizontal decomposition) on their received data then send the intermediate results to c_2 . After receiving the results, c_2 distributes it to the set of nodes n_{2i} (n_{21} , n_{22} , n_{23} and n_{24}). These nodes process data (vertical decomposition) and send the results (Level 1 data in Fig. 3(a)) to the next cluster head c_3 . The cluster head c_3 chooses a part of the results (corresponding to LL_1 in Fig. 3(b)) and distributes

it to the set of nodes n_{3i} (n_{31} , n_{32} , n_{33} and n_{34}). Those nodes run 1D wavelet transform algorithm of LL_1 sub-band then send the intermediate results to c_3 . After running the second 1D wavelet transform of LL_1 sub-band, c_3 process data and send the results (Level 2 data in Fig. 3) to the next cluster head c_4 . To be compatible with experiment results and depending on the image quality specified by the query (which is application-dependent), this procedure may continue on c_4 . The cluster head c_4 chooses a part of the results (corresponding to LL_2 in Fig. 3(c)) and distributes it to the set of nodes n_{4i} (n_{41} , n_{42} , n_{43} and n_{44}). Those nodes run 1D wavelet transform algorithm on their received data (LL_2 sub-band) then send the intermediate results back to c_4 with run 1D wavelet transform twice (corresponding to LL_2 sub-band) and code the results (Level 3 data in Fig. 3 (d)). This procedure may continue on c_7 and its following nodes until the final compressed image reaches the destination (sink) node. It should be noted that, as shown in Fig. 4, after the DWT, all the sub-bands are quantized by a single node (n_{5i}). The other nodes are put awake. Since the quantization represents about 5,5% of the total process time, In spite of resource constraints, an individual node has a sufficient power to realize the quantization block. Given that the Tier-1 coding represents about 43% of the total process time, the tasks partitioning optimize the network lifetime. After receiving the results, c_6 divides quantized sub-bands into a number of smaller code-blocks of equal size and send their processed results to set of nodes n_{6i} (n_{61} , n_{62} , n_{63} and n_{64}). In these nodes each code-block is entropy encoded independently to produce compressed bit streams.

III. 3. SYSTEM MODEL



For this study, we have adopted the 9/7 wavelet transforms implemented via lifting scheme (LS).

For each sample pixel, low-pass decomposition requires 8 shifts (S) and 8 adds (A) instructions whereas high-pass decomposition requires 2 shift and 4 add. There are two input lines in the architecture, one with all the even samples (x_{2i}) and the other with all the odd samples (x_{2i+1}). In this case, each pixel is read and written twice. Assuming that the input image size is of $M \times N$ pixels and that the image is decomposed into p resolution level, then 2D-DWT is iteratively applied $p-1$ levels. Using the fact that the image size decreases by a factor of 4 in each transform level, the total computational energy for this process can be represented as follows:

$$E_{DWT}(M, N, p) = M.N.(10.S + 12.A + 2.R_{mem} + 2.W_{mem}). \sum_{i=1}^{p-1} \frac{1}{4^{(i-1)}} \quad (1)$$

Where, S , A , R_{mem} , and W_{mem} represent the energy consumption for shift, add, read, and write basic 1-byte instructions, respectively [5].

The energy spent in entropy coding per bit is-

$$E_{ENT} = \delta \quad (2)$$

To analyze the degradation of image quality, we shall use the peak signal-to-noise ratio (PSNR) metric, which is defined (in decibels) as:

$$PSNR = 10 \times \log_{10} \frac{(2^q - 1)^2}{MSE} \quad (db) \quad (3)$$

Where, q is the number of bits per pixel (bpp) of the raw image, and MSE is the mean-square-error which defined by:

$$MSE = \frac{1}{M.N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [i(m,n) - \hat{i}(m,n)]^2 \quad (4)$$

Where, $i(m, n)$ is the pixel values of the original image, $\hat{i}(m, n)$ is the pixel values reconstructed image.

IV. EXPERIMENT RESULTS

In this section, we analyze the functional influence of the parameters initialized in the scenario proposed on Quality-of-Service (QoS) requirements on WSNs. Then, we study the impact of some parameter on the behavior of the distributed scheme to evaluate energy performance of image transmission. However, the deviation of these parameters to ensure a multi-level processing should affect other interesting factors which may influence the quality of the communication process such as:

- ✓ Execution time on the microcontroller (sensor node)
- ✓ Compression ratio
- ✓ PSNR

IV.1. IMPACT OF DWT ON COMPUTATION ENERGY

The energy concentration in the image by successive decomposition levels will allow decreasing the amount of information to be transferred to the destination. The computed quantity is divided by 4 at each decomposition level. This is a main objective to be

achieved, since the energy consumption in sensor nodes is proportional to the information quantity being transmitted.

Fig. 5. Input, Compressed and Reconstructed Image

As a result, reducing the quantity of transmitted data will extend the topological lifetime of WSNs. From the experiment, an afmsurf. tif is used as a test image. We first apply the decomposition in the horizontal direction. Since all even-positioned image pixels are decomposed into the low-pass coefficients and odd positioned image pixels are decomposed into the high-pass coefficients, the total computational energy involved in horizontal decomposition is :

$$E_H(M, N, p) = \frac{1}{2} M.N. (10.S + 12.A + 2.R_{mem} + 2.W_{mem}) \text{ --- (5)}$$

The average energy dissipated by every node is provided in Fig.6. The energy consumed by the nodes n_{1i} and $n_{2i}(i=1\dots4)$ to run 1D-DWT is of about 301mJ (by component) and 75mJ to run 1D wavelet transform algorithm of LL_1 sub-band (n_{3i}) corresponding to a 75% drop off. While the energy dissipated by every node n_{4i} is of about 18mJ.

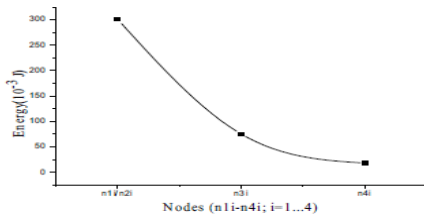


Fig. 6. Computational energy dissipated by every node

In this case, we were interested by analyzing the impact of the decomposition levels on the enhancement of the execution time. In Fig. 7, it's represented the execution time till five decomposition levels using the LS 9/7.

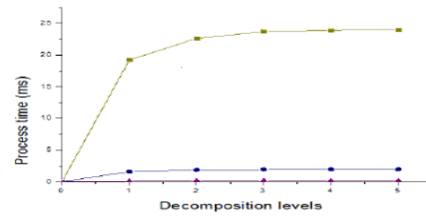


Fig. 7. Process time for 5 decomposition levels of LS 9/7

We have considered Lena image with different dimensions. The process time vary over decomposition levels and then reduced and become almost constant from the third decomposition level. Thus, the most of the image energy is located in LL sub-band. Therefore, an additional decomposition is useless and will waste energy without extracting more details. Fig. 8 illustrates the distribution of high-pass coefficients after applying tow levels wavelet transform to the 256*256 image. We notice that the high-pass coefficients values are very small. Indeed, 75% of the high-pass coefficients for level 1 are less than 5. Since the images have a low pass spectrum, the sub-bands transmission from cluster head c_4 to the sink must be transmitted with priority in order to save more energy.

Table.1. Measure basic element

	Compression ratio	PSNR	Execution time	Class of service
DWT decomposition level = 3 & Number of bit plane = 4	42.4	20.92	Low	Low image quality with low response time
DWT decomposition level = 3 & Number of bit plane = 5	22.8	27.34	Average	Low image quality with average response time
DWT decomposition level = 3 & Number of bit plane = 6	17.5	31.16	High	Average image quality with a high response time
DWT decomposition level = 3 & Number of bit plane = 7	15.64	33.5	High	High image quality with a high response time

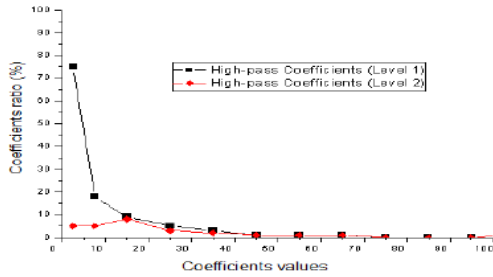


Fig.8. Distribution of high-pass coefficients

IV. 2. IMPACT OF ENTROPY ENCODING

Coding a 32*32 LL sub-band with 4 magnitude bit planes, the energy dissipated is of about 5 μ J (pass1) and 15 μ J (pass2), whereas energy dissipated by pass3 is inconsiderable. For a 32*32 LL sub-band with 5 magnitude bit planes, the average energy dissipated to run pass1 and pass2 is estimated to be 10 μ J each and the energy spent in pass3 is of about 2 μ J. So decrease in magnitude bit planes leads to lower image quality (table1) and less computation energy.

We have also studied the image transfer adaptability to WSNs through the analysis of some image compression parameters. This study has been achieved by analyzing the dependence between system lifetime and allocated memory, and helped to select the better compression rate as well as better image quality. The most important data are provided in the table 1.

V. CONCLUSION

In this paper, we have studied the problems of distributed image compression algorithm and its application in WSNs. The distributed image compression algorithm presented in this paper offers much flexibility at different process levels. These flexibilities are considered as dynamic parameters during the system to adapt the communication process. We have focused our

study on the design and evaluation of distributed scheme depending on the operating parameters at different process levels. We have explained the impact of these parameters on the WSNs operations. Adopting the proposed technique, should reduce required memory, minimize energy consumption and optimize network lifetime.

In this work the base idea of this approach is the communication cost of the nodes closer to the destination (more compressed) is smaller than the communication cost of its previous nodes on the path. In the future, further research must be focused on multipath routing which may enhance the performance of distributed image compression

REFERENCES

- [1] Zongkai Yang, Shengbin Liao, Wenqing Cheng, "Joint power control and rate adaptation in wireless sensor networks", *Ad Hoc Networks* 7(Elsevier) (2009) 401–410.
- [2] Mohammad Hossein, Yaghmaee, Donald A. Adjeroh, "Priority-based rate control for service differentiation and congestion control in wireless multimedia sensor networks", *Computer Networks* (Elsevier) (2009).
- [3] Huaming Wu, Alhussein A. Abouzeid, "Energy efficient distributed image compression in resource-constrained multihop wireless networks", *Computer Communication* (Elsevier) 28 (14) (2005) 1658–1668.
- [4] W. Zhang, Z. Deng, G. Wang, L. Wittenburg, Z. Xing, "Distributed problem solving in sensor networks", *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems*, ACM Press, 2002, pp. 988–989.
- [5] Vincent Lecuire, CristianDuran-Faundez, and Nicolas Krommenacker, "Energy-Efficient Transmission of Wavelet-Based Images in Wireless Sensor Networks", *Eurasip journal on Image and Video Processing*, 11 pages, 2007.
- [6] Qin Lu, Wusheng Luo, Jidong Wang, Bo Chen, "Lowcomplexity and energy efficient image compression scheme for wireless sensor networks", 1389-1286- 20 *Computer Networks* (Elsevier) 52 (2008) 2594–2603.

- [7] Zongkai Yang, Shengbin Liao, Wenqing Cheng, “Joint power control and rate adaptation in wireless sensor networks”, *Ad Hoc Networks (Elsevier)* 7 (2009) 401–410.
- [8] D.Vijendra Babu, Dr.N.R.Alamelu, P.Subramanian, N.Ravikannan, “EBCOT using Energy Efficient Wavelet Transform”, *International Conference on Computing, Communication and Networking (ICCCN 2008)*, 978- 14244-3595- IEEE.
- [9] R. Wagner, R. Nowak, and R. Baraniuk, “Distributed image compression for sensor networks using correspondence analysis and super-resolution”, *Proceedings of IEEE International Conference on Image Processing (ICIP)*, volume 1, pages 597–600, September 2003.
- [10] N. Boulgouris and M. Strintzis, “A family of waveletbased stereo image coders”, *IEEE Transactions on Circuits and Systems for Video Technology*, 12(10):898–203, October 2002.
- [11] Huaming Wu and Alhussein A. Abouzeid, “Energy efficient distributed JPEG2000 image compression in multihop wireless networks”, *4th Workshop on Applications and Services in Wireless Networks (ASWN 2004)*, pages 152–160, August 2004.
- [12] Min Wu and Chang Wen Chen, “Multiple bitstream image transmission over wireless sensor networks”, *Proceedings of IEEE Sensors*, volume 2, pages 727–731, October 2003.
- [13] L. Ferrigno, S. Marano, V. Paciello, and A. Pietrosanto, “Balancing computational and transmission power consumption in wireless image sensor networks”, *IEEE29 International Conference on Virtual Environments, Human-Computer Interfaces, and Measures Systems (VECIMS 2005)*, Giardini Naxos, Italy, July 2005.
- [14] A. Wang. A. Chandrakasan, “Energy efficient system partitioning for distributed wireless sensor networks”, *Proceedings of the International Conference on Acoustics, Speech, and Signal processing (ICASSP-2001)*, Salt Lake City, Utah, 2001.
- [15] S.S. Pradhan, J. Kusuma, K. Ramchandran, “Distributed compression in a dense microsensor network”, *IEEE Signal Processing Magazine* 19 (2) (2002) 51–60.
- [16] B. Song, O. Bursalioglu, A. Roy-Chowdhury, and E. Tuncel. Towards a distributed video compression algorithm, University of California, Riverside, <http://www.dvsp.ee.ucr.edu/>
- [17] Qin Lu, Wusheng Luo, Jidong Wanga, Bo Chen, “Lowcomplexity and energy efficient image compression scheme for wireless sensor networks”, *Computer Networks (Elsevier)* 52 (2008) 2594–2603.