International Conference on Wireless and Ubiquitous Systems
8-10 October 2010, Sousse, TUNISIA

Energy-Efficient Wavelet Image Compression in Wireless Sensor Network

Mohsen Nasri, Abdelhamid Helali, Halim Sghaier & Hassen Maaref
Laboratoire de Micro-Optoélectronique et Nanostructures(LMON)
Faculté des Sciences de Monastir / Institut Supérieur d'Informatique et de Mathématiques de Monastir
Tunisia
(nasrimohsen@yahoo.fr, abdelhamid.helali@isimm.rnu.tn, halim.sghaier@isimm.rnu, hassen.maaref@fsm.rnu.tn)

***Abstract* - In the recent years, the wireless technology would have known an exponential growth, which has an impact on developing and improving the field of telecommunications beyond the means of transmission wire to the radio frequency communication. The Wireless Sensor Network (WSN) is enrolled in this context. It's a collection of component (nodes) organized into a cooperative network. The main components of this network are tiny battery powered cameras with wireless communication capability. Therefore, image transfer in WSNs presents major challenge which raises issues related to its representation, its storage and its transmission. However, communication of image content has several bottlenecks, including limited bandwidth of cellular networks, restricted computational power, limited storage capability, and battery constraints of the appliances. In this paper, we address the energy, system lifetime and bandwidth bottlenecks of image communication. We present an efficient adaptive compression scheme that can significantly minimize the energy required for wireless image communication while meeting bandwidth constraints of wireless network and image quality. Based on Discrete Wavelet Transform, we propose an efficient image compression scheme, enabling significant reduction in computation energy needed with minimal degradation of image quality. Simulation results are done with C++ and show that the proposed scheme optimizes network lifetime, reduces significantly the amount of required memory and minimizes both (i) computation energy, by reducing the computation needed to compress an image and (ii) communication energy, consumed by the RF component which is proportional to the number of transmitted bits.**

Keywords: Wireless Sensor Network; Image compression; Energy optimization, Skipped High-Pass Sub-band technique.

1. INTRODUCTION

A wireless sensor network (WSN) is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions. The development of such networks was originally motivated by military applications such as battlefield surveillance. However, wireless sensor networks are now used in many civilian application areas, including environment and habitat monitoring, healthcare applications, home automation, and traffic control [1-2]. As depicted in Fig. 1, data collected by sensors is transmitted to a special node equipped with higher energy and processing capabilities called "Base Station" (BS) or "sink". The BS collects filters and aggregates data sent by sensors in order to extract useful information. One of the major challenges in enabling image transfer services will be the need to process and wirelessly transmit very large volumes of data. This will impose severe demands on the battery resources of image-based applications as well as the bandwidth of the wireless network. Typically, images are compressed in order to save consumed energy.

In this context, image transmission improvement over WSN is mainly done by the implementation of distributed image compression algorithm embedded in order to reduce the number of bits needed to represent an image by removing the spatial and spectral redundancies, thus reducing the energy consumption. The distributed image compression enables the sharing of computation load among sensors. This technique is based on the fact that an individual node does not have sufficient computational power to completely compress a large volume of image data to meet the application requirements; this is not possible unless the node distributes the computational task among other nodes. In this paper, we propose an adaptive image transmission approach in WSN, based on wavelet image transform called *SHPS* (Skipped High-Pass Sub-band). This technique is being used because of the small high-pass coefficients values. In this approach the high-pass coefficients do not have to be computed reducing the number of executed operations and therefore save computation energy required during the wavelet image compression process. This paper is organized as follows: Section 3 describes general architecture of networked wireless sensor devices. Operating phases of sensors nodes is proposed in section 4. Section 5 describes image processing in WSNs. Experimental results are shown in section 6. Finally, section 7 concludes this work.

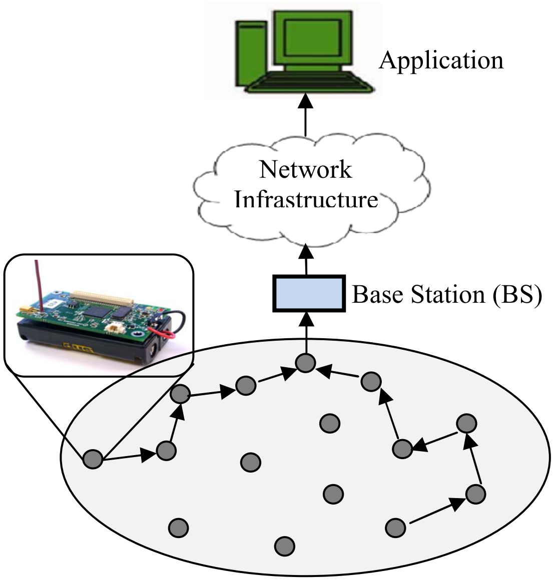


Fig.1. Sensor Network

2. RELATED WORK

The image compression techniques and processing algorithms related to wireless can be categorized into two groups: Local processing and compression, and distributed processing and compression. In this section, we investigate the various proposals under these categories especially for the wireless sensor network (WSN) deployment scenarios.

2.1. A LOCAL PROCESSING AND COMPRESSION

In this technique, a single source coding is used in image coding where each source codes its information independently of other sources. Some works have demonstrated that the complexity of certain compression algorithms leads to greater power consumptions than the simple transmission of the uncompressed image. For instance, Ferrigno et *al*. presented in [4] a platform to evaluate the performance of different traditional algorithms for image compression in a single sensor node. They analyzed five algorithms: JPEG2000, SS, DCT, SPITH and JPEG. Results show that SS is the unique algorithm which presents energy savings with respect to the no-compression case, allowing a power reduction of about 29%. The mechanism proposed in [5] uses a scheme based in SPIHT coding of data blocks generated from parent-child relation chips of wavelet coefficients. This parent-child relationship is performed in order to reinforce SPIHT fragilities in bit error transmission cases. The adopted approach in [6] has introduced a power aware technique that incorporates the local compression JPEG2000 standard. They formulated the image transmission problem as an optimization problem and proposed a heuristic algorithm called MTE (Minimize Total Energy).

2.2. A DISTRIBUTED PROCESSING AND COMPRESSION

Distributed processing refers to the compression of multiple correlated sensor outputs from sensors with limited or no cooperation and joint decoding at a central decoder. Several works was proposed in this study. In resourced-constrained WSNs, Huaming Wu et al. noticed the high energy consumption of JPEG2000 first [7]. They presented two methods in order to reduce energy consumption during image compression. In the first method image is partitioned into n number of blocks along the rows to perform 1-D wavelet transform. In the second phase image is portioned into m number of block to perform 1-D wavelet transform on column. The second method, image tilling technique is used with wavelet compression. Wagner *et al.* [8] proposed a distributed source coding scheme for images captured by sensor nodes having overlapping fields of view. The approach uses a technique similar to stereo-image compression [9] to identify overlap in the images of neighboring sensor nodes. In [10,11] a distributed image compression problems exploit correlations between data at close-by sensors in order to jointly compress or fuse the correlated information resulting in savings in communication energy.

Other research has been focused on image processing techniques in wireless sensor networks. By mapping individual sensors as pixels in an image, Devaguptapu [12] examined cleaning of uncorrelated sensor noise, and the decentralized detection of edges. Ganesan et al. [13] have proposed a generalized hierarchical architecture for multiresolution querying of regularly placed sensor networks that is based on wavelet transforms. Servetto [14] also exploits wavelet transforms to decorrelate sensor data to address the sensor broadcast problem where every sensor observes only one pixel. These works focus on the correlation between sensor nodes.

The goal of image compression related studies is to minimize the energy required without a trade-off between energy consumed and image quality. In this paper, we introduce a novel technique which optimizes computation energy consumed with acceptable compromise on image quality.

3. THE NETWORKED WIRELESS SENSOR DEVICES

A wireless sensor networks consist of small autonomous sensor nodes. A basic sensor node comprises five main components (Fig.2):

Microcontroller**:** A microcontroller allows processing all the relevant data, capable of executing arbitrary code.

Memory: Some memory is used to store programs and intermediate data; usually, different types of memory are used for programs and data.

Sensors: devices that can observe or control physical parameters of the environment.

A radio chip**:** Turning nodes into a network requires a device for sending and receiving information over a wireless channel.

Power supply: The supply unit has to provide the necessary energy for the functioning of the sensor set. The choice of the energy source is thus going to depend on the autonomy and features required by the application.

Due to their low-cost and low-complexity nature, sensors node are characterized by several constraints, such as a short transmission range, poor computation and processing capabilities, low reliability and data transmission rates, and a limited available energy.

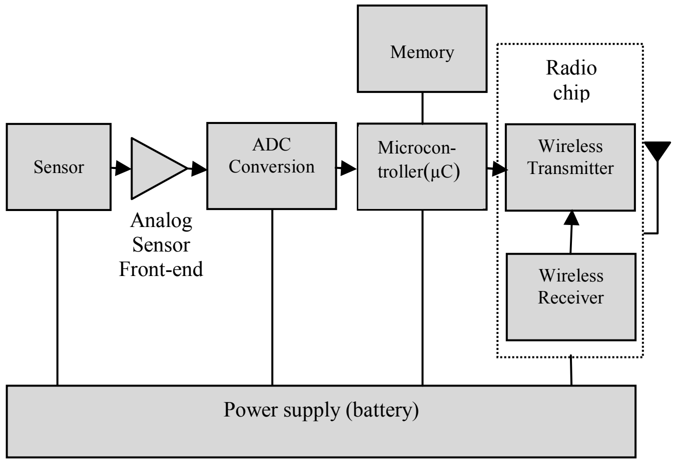


Fig.2.Synoptic scheme of an autonomous sensor node

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 image. The most important requirements of image transmission in WSNs are: Image sensing, allocated memory and image processing.

4. THE OPERATING PHASES OF SENSOR NODES

The energy consumption was depending on the node operation mode. It's possible, to break up the node operation into various phases. In the majority wireless applications, the node follows an operation cycle which is depending on the concerned application. During this cycle, it's possible to manage independently each element of this node following the required specifications by the application. It's thus possible to define several operation phases. Fig.3 shows these node operating phases according to time as well as the elements under operation for each phase in the case more running.

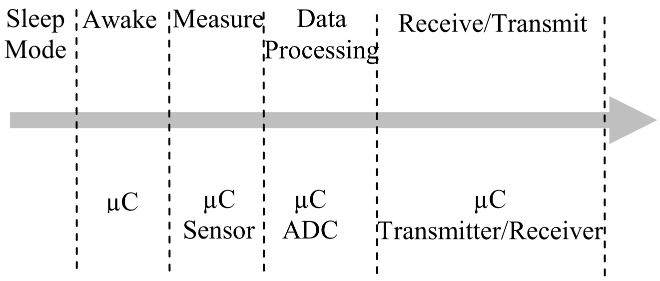


Fig.3. Operating phases of sensors node

✓ **Sleep State**: During sleep states, all the blocks of the sensor node are switched off. In order to conserve energy, it is desirable to maximize the time a node spends in sleep mode. In the case, each sensor selects its own schedule period T and sleeps for a duration of T'= random (0, T) before it wakes up again.

✓ **Awake:** Whenever a node becomes active, it broadcasts a beacon message through the control channel, advertising to its neighbors that it is awake. Then, it checks if there is any packet generated by it to be transmitted.

✓ **Measure:** During this phase, the node has as a function to take one or more measurements which will have then to be converted into numerical data by analog-to-digital converters.

✓ **Data Processing:** This phase includes the conversion of measurement from the sensor by the analog-to-digital converter then its treatment by the microcontroller: working of data, adaptation to the communications protocol, and coding. The duration of this phase will depend on the execution speed of the microcontroller, the conversion time and the complexity of the used protocol.

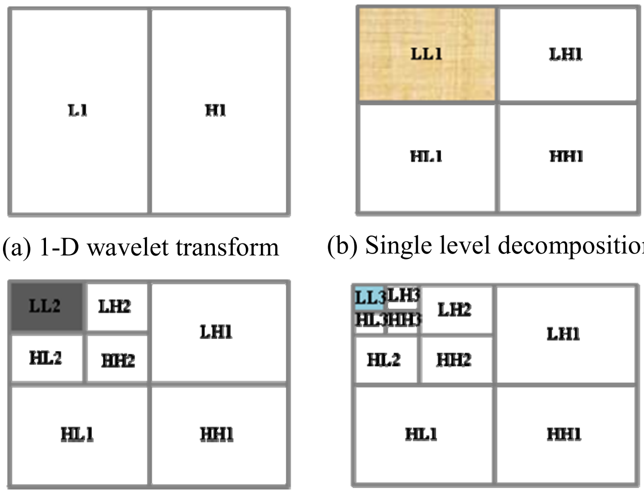
✓ **Receive/Transmit**: A sensor in this state performs the tasks of receiving and transmitting packets.

5. THE IMAGE TRANSMISSION TO 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. In this paper, the proposed image transmission scheme is based on wavelet image transform.

5.1 THE WAVELET TRANSFORM

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)) facilitates progressive transmission of images. Because of their inherent multiresolution nature wavelet coding schemes are especially suitable for applications where scalability and tolerable degradation are important. Theoretically, Discrete Wavelet Transforms (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). 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. The information of LL_2 is used for the third level transform. We refer to the sub-band LL_i as a low-resolution sub-band and high-pass sub-bands LH_i, HL_i, HH_i as horizontal, vertical, and diagonal sub-band respectively since they represent the horizontal, vertical, and diagonal residual information of the original image. An example of three-level decomposition into sub-bands is shown in the Fig. 4.



(a) 1-D wavelet transform (b) Single level decomposition

(c) Two level decomposition (d) Tree level decomposition

Fig.4. Illustration of wavelet spectral decomposition.

To save computation energy, we propose an adaptive image transmission approach in WSNs consisting of technique to skip computation of certain high-pass coefficients of an image. This technique attempts to conserve energy by skipping the least significant sub-band. This technique is called "*SHPS*: Skipped High Pass Sub-bands".

Fig.5 illustrates the distribution of high-pass and low-pass coefficients after applying 1-D wavelet transform to the 512*512 Lena image. We observe that the high-pass coefficients are generally represented by small integer values. Indeed, the most of the high-pass coefficients are less than 0.2. Since the image presents a low pass spectrum, high-pass filtering is skipped. Therefore, high-pass coefficients not computed resulting in a minimal image quality loss. Since the *SHPS* technique is implemented by making specific modifications on the wavelet transform, all the images can still keep main information as 'Lena' when the high pass sub-bands are skipped.

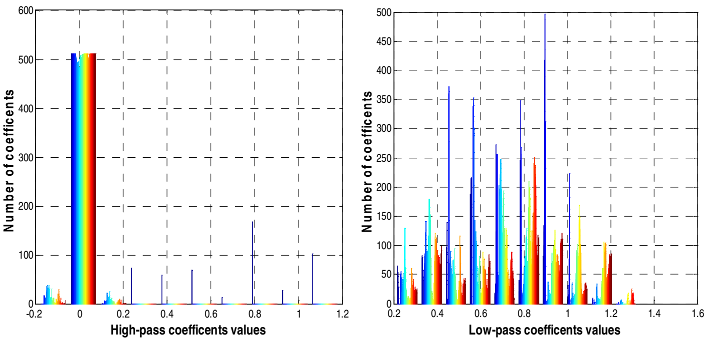


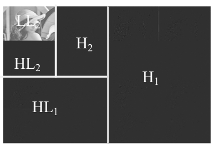
Fig.5.Numerical distribution of high-pass/low-pass coefficients after wavelet transform through 1-D DWT

Using the estimation technique presented, we have developed our *SHPS* technique which conserves energy by skipping the computation of high-pass coefficients. This technique attempts to conserve energy by skipping the least significant sub-band H_i in the vertical direction in each transform level. Therefore, the low-pass sub-bands (Li) resulting from the horizontal direction is further decomposed in the vertical direction, leading to LLi and LHi sub-bands. The *SHPS* technique reduces some computation loads during the transform steps by skipping tow out of every four sub-bands. For each vertical decomposition, only the LL_i and LH_i sub-bands are computed as shown in Fig.6.

(a) Imput 512*512 Lena Image

(b) 1-D DWT

(c) Level 1-SHPS technique



(d) Level 2-SHPS technique

Fig. 6. The SHPS technique* compression *on 512*512 Lena image

5.2. THE DISTRIBUTED IMAGE COMPRESSION

The proposed architecture of image compression is based on distributing the workload of Wavelet transform-SHPS technique to several groups of nodes along the path from the source to the sink. The main idea in the design of distributed task of image compression is based on data exchange. In this proposal, data is broadcasted to all processors to speed up the execution time which may optimize network lifetime and decrease the consumed energy. A routing algorithm is assumed to be in place and nodes are self-organized into a two-tiered architecture [15].

After receiving a query from a source node s, the cluster head c_1 selects a set of nodes p_{1i} in the cluster which will take part in the distributed wavelet transform then informs s. The source transmits the original image to p_{1i}. Those nodes run 1D wavelet transform algorithm (horizontal decomposition) on their received data then send the results to c_2. Cluster head c_2 selects the low-pass sub-band (L_1) and forwards it to the set of nodes p_{2i}. The remaining part of the image (H_1 in Fig. 6(b)) is coded and sent to the next cluster head c_3. The p_{2i} nodes also send their processed results (LL_1 and HL_1 in Fig. 6(c)) to c_3 after running 1D wavelet transform twice. Cluster head c_3 combines the sub-bands (LL_1, HL_1 and H_1 in Fig. 6(c)) then selects a part of LL_1 sub-band (Fig. 6(c)) and forwards it to the set of nodes p_{3i}. Depending on the image quality specified by the wireless application, this procedure may continue on c_n and its following nodes until the final compressed image reaches the destination (sink) node. An example of distributed cluster-based compression is shown in Fig.7.

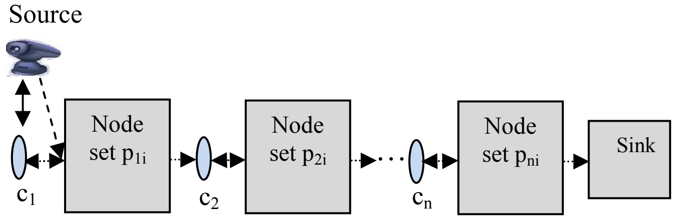


Fig.7.The distributed compression

5.3. ANALYSIS OF ENERGY CONSUPTION

For this study, the adopted technique is based on the Cohen-Daubechies-Favreau (CDF) 9/7 DWT implemented via lifting scheme (LS). The main property of the wavelet filter is that it has good localization and symmetric properties, which allow for simple edge treatment, high-speed computation, and high quality compressed image. In addition, this filter is amenable to energy efficient hardware implementation because it consists of binary shifter and integer adder units rather than multiplier/divider units. The lifting scheme makes to minimize the number of operations as well as the memory occupation, by carrying out low-pass and high-pass filtering simultaneously. Using this filter, 8 shift and 8 add operations are required to convert the sample image pixel into a low-pass coefficient. Similarly, high-pass decomposition requires 2 shift and 4 adds. We model the energy consumption of the low/high-pass decomposition by counting the number of operations and denote this as the *computational load*. Thus 8S + 8A units of computational load are required in a unit pixel of the low-pass decomposition and 2S + 4A units for the high-passes. Assuming that the input image size is of M*N pixels and that the image is decomposed into *p* resolution level, and 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 load can be represented as follows:

$$C_{CDF\ 9/7\ DWT} = MN\,(10\,S + 12\,A)\sum_{i=1}^{p-1}\frac{1}{4^{(i-1)}} \qquad (1)$$

Besides various arithmetic operations, the transform step involves a large number of memory accesses. Since the energy consumed in external and internal data transfers can be significant, we estimate the *data-access load* by counting the total number of memory accesses during the wavelet transform. At a transform level, each pixel is read and written twice. Hence, with the same condition as the above estimation method, the total data-access load is given by the number of read and writes operations:

$$C_{read} = C_{write} = 2MN(W_{mem} + R_{mem})\sum_{i=1}^{p-1}\frac{1}{4^{(i-1)}} \quad (2)$$

The overall computation energy is computed as a weighted sum of the computational load and data-access load:

$$E_{DWT}(M,N,p) = MN(10S + 12A + 2R_{mem} + 2W_{mem})\sum_{i=1}^{p-1}\frac{1}{4^{(i-1)}} \quad (3)$$

Where, S, A, R_{mem}, and W_{mem} represent the energy consumption for shift, add, read, and write basic 1-byte instructions, respectively [16].

Image quality is measured using the peak signal-to-noise ratio (PSNR) metric, which is defined (in decibels) as

$$PSNR = 10.\log_{10}\frac{(2^b - 1)^2}{MSE} \quad (dB) \quad (4)$$

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

$$MSE = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}\left[i(m,n) - \hat{\imath}(m,n)\right]^2 \quad (5)$$

Where, $i(m,n)$ and $[\hat{\imath}(m,n)]$ are the pixel values of the original [reconstructed] image.

6. RESULTS

In this section, we report on simulation results conducted to evaluate the energy savings made possible by using the proposed technique. In particular, we report on the savings in computation and communication energy using the *SHPS* technique, and discuss their impact on image quality.

6 .1. EFFECT ON COMPUTATION ENERGY

To estimate the energy efficiency of the proposed technique (*SHPS*) presented, we measure the computational and data access loads using the same method outlined in section 5.3. We assume the skipping technique is applied to the first E transform levels out of the *p-1* total transform levels. This is because the advantage of skipping high-pass coefficients is more significant at lower transform levels.

Using *SHPS* technique, the computation load during the row transform is the same as with the *CDF 9/7 DWT* algorithm. However, during the column transform the high-pass sub-band (HH) and (LH) are not computed, resulting in less computed operation and hence saving computational load. The computation load saving is given by:

$$\underbrace{\frac{1}{4}MN(8A+8S)}_{LH} + \underbrace{\frac{1}{4}MN(4A+2S)}_{HH} = \frac{1}{4}MN(12A+10S) \quad (6)$$

(25% compared to the *CDF 9/7 DWT*).

Therefore, the total computational load when using this technique is represented as:

$$Computational\ load:$$

$$C_{SHPS} = MN\frac{(30S + 36A)}{4}\sum_{i=1}^{E}\frac{1}{4^{(i-1)}} + MN(12A + 10S)\sum_{i=E+1}^{p-1}\frac{1}{4^{(i-1)}} \quad (7)$$

Because the high-pass sub-band resulting from the row transform is not computed during the column transform, we can save on a half of "write and read" operations (25% savings) corresponding to $\frac{1}{2}MN(2R_{mem} + 2W_{mem})$ of data-access load. Therefore, the *SHPS* technique reduces some data-access loads during the transform steps by skipping tow out of every four sub-bands. The total data-access load is given by:

$$Data - acess\ load:$$

$$C_{Read-SHPS} = C_{Write-SHPS} = \frac{3}{2}MN(2R_{mem} + 2W_{mem})\sum_{i=1}^{E}\frac{1}{4^{(i-1)}} + MN(2R_{mem} + 2W_{mem})\sum_{i=E+1}^{p-1}\frac{1}{4^{(i-1)}} \quad (8)$$

6 .2. EFFECT ON COMPUTATION ENERGY AND IMAGE QUALITY

In this section, we used the Lena image sample, and measured the saving computation energy and the PSNR of the compressed image. The results are presented in Fig. 8.

We observe that the *SHPS* technique leads to significant energy savings at nominal loss in image quality. This technique can save up to 25% for level 1 decomposition and 33% for level 3 decomposition. However, the computation energy of *SHPS* technique is associated with loss in image quality: PSNR=26dB for level 1 and PSNR=24dB for level 3.

The above experiments demonstrate that depending on the image quality desired by a wireless service, and the state of the battery of the wireless appliances, by applying the *SHPS* technique at different levels, different trade-offs can be obtained between the image quality obtained and the energy expended in compressing the image and transmitting the compressed image.

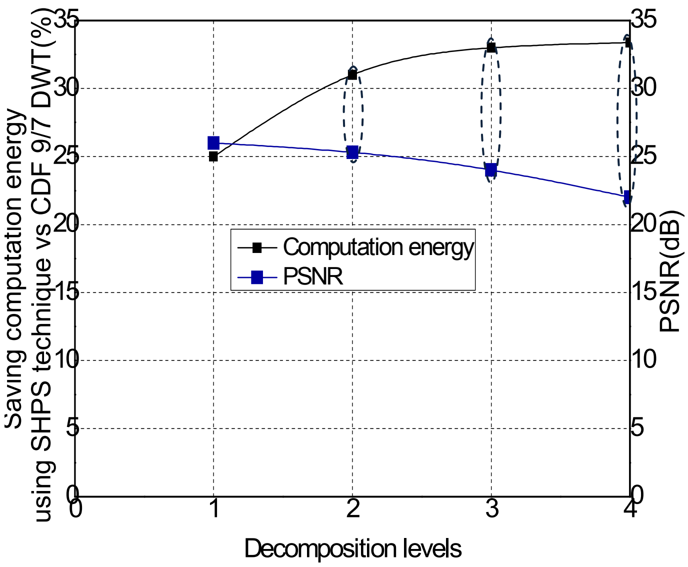


Fig. 8. Effects of SHPS technique on image quality and computation energy

To get an idea of the impact on image quality, we present visual comparisons of two versions of the Lena image obtained. The image shown in Fig.9 (a) is obtained by using the *CDF 9/7 DWT*, while the image shown in Fig. 9(b) is obtained using the *SHPS* technique through level 3. The PSNRs of the two images are 29 dB (*CDF 9/7 DWT*) and 24 dB (*SHPS*) respectively.

(a) *CDF 9/7 DWT*: PSNR=29 (b) *SHPS* technique: PSNR=24

Fig. 9. The image quality after, CDF 9/7 DWT and SHPS techniques using the Lena 512*512 grayscale image.

6 .3. EFFECT OF DISTRIBUTED COMPRESSION ON COMMUNICATION ENERGY.

In this study, we report results of using distributed image compression using *SHPS* technique to minimize communication energy consumed in reception. Transceiver energy dissipation model [17] is used. The energy consumed in reception per bit is

$$E_{RX} = \varepsilon_e \qquad (7)$$

Where, ε_e is energy consumed per bit. The parameter values for wireless communication energy model (7) are $\varepsilon_e = 50\,10^{-9}\ J$ as for example in [14].

The communication energy for this technique is estimated from the size of the transmitted sub-band. In this case, we were interested by analyzing the energy consumed in reception, since the transmission is realized by the cluster head which is more powerful than the sensor node. From Fig.10, we note that the energy consumed by the nodes set p_{1i} to receive row image is of about 13 10^{-3} J each one and 6 10^{-3}J to receive L_1 sub-band (p_{2i}) corresponding to a 50% drop off. While the energy consumed by every node p_{3i} to receive LL_1 sub-band is of about 3.2 10^{-3}J. Therefore, the *SHPS* technique results in significant communication energy savings. For each transform level that the *SHPS* technique is applied, only L_i and LL_i sub-bands are sent to node set p_{ni} leading to less information to be transmitted over the wireless channel.

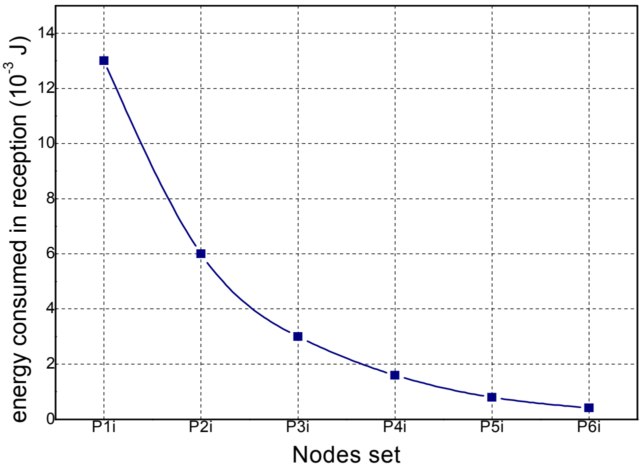


Figure.10. The communication energy dissipated in reception by every node, the distributed cluster-based compression using four nodes in each cluster (i=1…4). Three levels of SHPS-Wavelet decomposition are used.

7. CONCLUSION

Image transfer in WSNs requires very large amounts of data to be transmitted, creating tremendously high energy and bandwidth requirements that cannot be fulfilled by limited growth in battery technologies, or restricted computational power and limited storage capability. This paper presents a potential solution to the emerging problem, by developing a novel technique for image compression called *SHPS*. Its mean objective is to optimize computation energy consumed with acceptable compromise on image quality. In the future, further research must be focused on multipath routing which may enhance the performance of the distributed image compression.

REFERENCES

[1] D. Estrin, Sensor network research, "emerging challenges for architecture systems, and languages, in: C. Norris, J.J.B. Fenwick (Eds.)", Proceedings of the 10th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS-X), 10 of ACM SIGPLAN Notices vol. 37, ACM Press, New York, 2002, pp. 1–4.

[2] A.E. Gamal, Collaborative Visual Sensor Networks, 2004, http:// mediax.stanford.edu/projects/cvsn.html.

[4] 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), Giardini Naxos, Italy, July 2005.

[5] 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.

[6] 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.

[7] H.M. Wu, A.A. Abouzeid, Energy, "efficient distributed image compression in resource-constrained multihop

wireless networks", Computer Communication (Elsevier) 28 (14) (2005) 1658–1668.
[8] 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.
[9] N. Boulgouris and M. Strintzis. "A family of wavelet-based stereo image coders". IEEE Transactions on Circuits and Systems for Video Technology, 12(10):898–203, October 2002.
[10] 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.
[11] S.S. Pradhan, J. Kusuma, K. Ramchandran, "Distributed compression in a dense microsensor network", IEEE Signal Processing Magazine 19 (2) (2002) 51–60.
[12] D. Devaguptapu, B. Krishnamachari, "Applications of localized image processing techniques in wireless sensor networks", SPIE's 17th Annual International Symposium on Aerospace/Defense Sensing, Simulation, and Controls (Aerosense'03), Orlando, Florida, 2003.
[13] D. Ganesan, B. Greenstein, D. Perelyubskiy, D. Estrin, J. Heidemann, "An evaluation of multi-resolution storage for sensor networks", Proceedings of the First International Conference on Embedded Networked Sensor Systems, ACM Press, 2003, pp. 89–102.
[14] S.D. Servetto, "Sensing lena–massively distributed compression of sensor images", Proceedings of the IEEE International Conference on Image Processing (ICIP) (special session on 'Distributed Source Coding'), Barcelona, Spain, 2003.
[15] S. Bandyopadhyay, E.J. Coyle,"An energy-efficient hierarchical clustering algorithm for wireless sensor networks", INFOCOM, 2003.
[16] Vincent Lecuire, Cristian Duran-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.
[17] H. Wu, A.A. Abouzeid, "Energy efficient distributed JPEG2000 image compression in multihop wireless networks" ASWN 2004. pp 152-160.