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Efficient JPEG 2000 Image Compression Scheme for Multihop Wireless Networks

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Abstrak

Ketika menggunakan jaringan sensor nirkabel untuk transmisi data waktu-nyata, beberapa poin kritis seharusnya dipertimbangkan. Daya komputasi yang terbatas, memori yang berkurang, bandwidth yang sempit dan pasokan energi yang sangat terbatas pada node sensor. Karenannya, pemaksimalan umur hidup jaringan dan peminimalan konsumsi energi selalu menjadi tujuan optimasi. Guna mengatasi keterbatas komputasi dan energi setiap node sensor selama transmisi citra, sebuah skema transportasi citra yang efisien energi diusulkan, mengambil keuntungan dari JPEG2000 tetap dengan standar kompresi citra menggunakan MATLAB dan C dari Jasper. JPEG2000 menyediakan satu set fitur praktis, yang belum tersedia pada standar sebelumnya. Fitur-fitur ini dicapai menggunakan teknik: transformasi wavelet diskrit (DWT), dan penyandian blok terbenam dengan dengan pemotongan dioptimalkan (EBCOT). Kinerja skema transportasi citra yang diusulkan diselidiki sehubungan dengan kualitas citra dan konsumsi energi. Hasil simulasi yang dihadirkan menunjukkan bahwa skema yang diusulkan mengoptimalkan waktu hidup jaringan dan mengurangi secara signifikan jumlah memori yang diperlukan dengan menganalisis pengaruh fungsional dari masing-masing parameter algoritma kompresi citra terdistribusi ini.

Kata kunci: *jaringan sensor nirkabel,JPEG2000, komprosi citra terdistribusi, konservasi energy*

Abstract

When using wireless sensor networks for real-time data transmission, some critical points should be considered. Restricted computational power, reduced memory, narrow bandwidth and energy supplied present strong limits in sensor nodes. Therefore, maximizing network lifetime and minimizing energy consumption are always optimization goals. To overcome the computation and energy limitation of individual sensor nodes during image transmission, an energy efficient image transport scheme is proposed, taking advantage of JPEG2000 still image compression standard using MATLAB and C from Jasper. JPEG2000 provides a practical set of features, not necessarily available in the previous standards. These features were achieved using techniques: the discrete wavelet transform (DWT), and embedded block coding with optimized truncation (EBCOT). Performance of the proposed image transport 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: *distributed image compression, energy conservation, JPEG2000, wireless sensor networks*

1. Introduction

Recently wireless sensor network (WSN) has become one of the most interesting networking technologies since it can be deployed without communication infrastructures [1]. The WSNs are based on small sensor nodes and a sink as shown Figure 1. The main characteristic of such networks is nodes with scarce resources. These nodes consist 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. So, sensor nodes are embedded

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system witch sense their environment, collect sensed data and transmit it to the sink in an autonomous way using multi-hop communication.

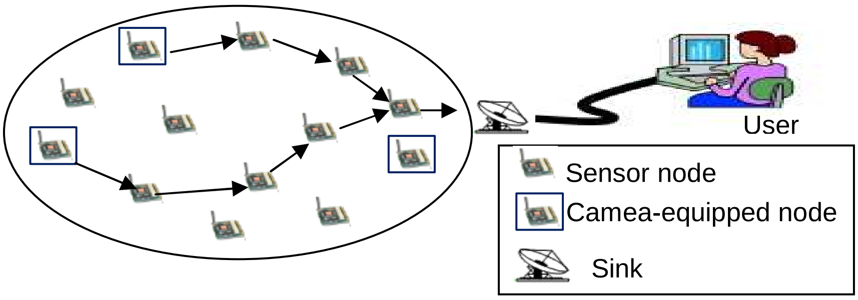

Figure1. Sensor network architecture.

However, they are energized by small and irreplaceable batteries. Under such energy constraint condition, sensor nodes can only transmit a finite number of bits in their lifetime. Consequently, energy consumption and data transmission are always considered together in WSNs. Therefore, approaches to optimize data transmission are a critical issue. For image-based applications, one uses a wireless sensor network whereby the nodes are camera-equipped [2]. Since, heterogeneous sensor nodes are battery-powered; the image transfer in WSNs presents major challenge which raises issues related to its representation, its storage and its transmission [3]. In this context, 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 the 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.

Image compression is a well-established research field, but sensor networks present a context in which new design issues have to be addressed. The main characteristic of such networks is nodes which are mainly characterized by limited energy. Therefore, the primary focus on energy, computational power, and allocated memory call for new compression and processing algorithms. The image compression techniques and processing algorithms in a wireless sensor network are classified in two categories: (i) local processing and compression, and (ii) distributed processing and compression.

Local algorithms are useful only when the complete processing, including image compression and transmission, is less energy consumming than the single transmission of uncompressed image. 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.* have presented in [4] a platform to evaluate the performance of different traditional algorithms for image compression in a single sensor node. They have analyzed five algorithms: joint photographic experts group (JPEG), spread spectrum (SS), discrete cosine transform (DCT), set partitioning in hierarchical trees (SPITH) and JPEG2000. 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] uses a local compression of JPEG2000 standard. In this approach, Huaming W *et al.* have introduced a power aware technique that incorporates the JPEG2000 standard to compress captured images from wireless camera nodes.

In [7] a distributed image compression using the JPEG2000 standard is proposed. The basic idea is the distribution of the wavelet transform processing workload between various nodes. This paper proposes an original technique to reduce power consumption of the sensor network during image transmission. The flexibility of a distributed image compression algorithm is used to adapt the communication process.

2. The Proposed Method

Nowadays, more and more multimedia applications integrate wireless transmission functionalities. Due to their ease of deployment, WSN has many applications such as military application, surveillance, localization, and tracking. The main task of a sensor node is to sense the environment and report what happens. Data collected by sensor nodes are usually routed back to a sink by a multiple-hop communication [8]. In order to make image transmissions possible via energy preservation and allocated memory based heuristic. We use an image request based scenario as shown in Figure 2.

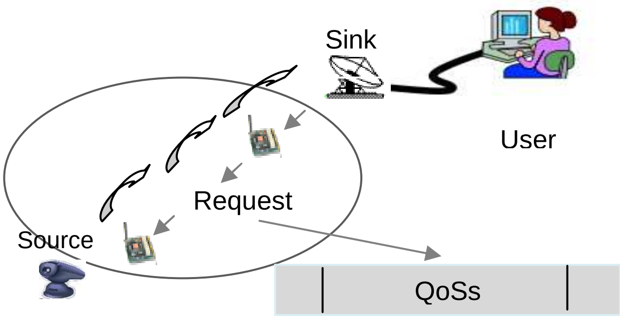

Figure 2. Scenario used for the image request

In this scenario a request specifying the necessary constraints of quality of security service (QoSS) is required to initiate image transmission scheme with the operation parameters such as: (peak signal to noise ratio) PSNR and compression ratio. When sending an image request, the user specifies the desired parameters. In this investigation, the communication environment is assumed to be contention-free and error-free. In this approach, we propose a distributed image compression scheme where nodes compress an image while forwarding it to the sink subject to a specific image quality requirement and optimize network lifetime.

In this study, the proposed image transmission scheme is based on wavelet image transform. The structure of the transform coder is illustrated in Figure 3. The main objectives achieved by this image compressing system are: Progressive transmission, progressive quality, reduced allocated memory, minimized energy consumption, and optimized network lifetime.

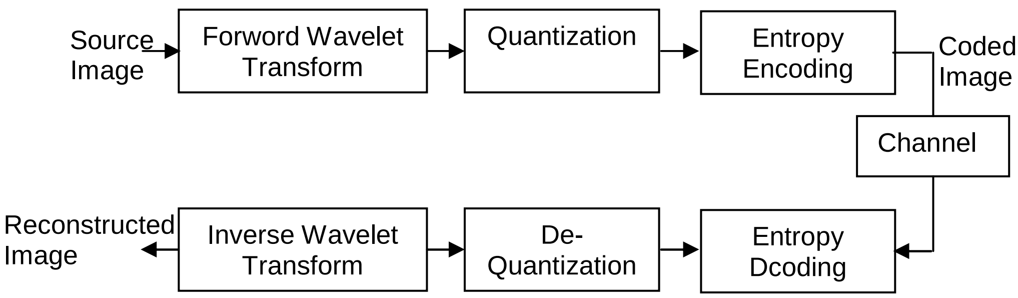

Figure 3. Functional block diagram of JPEG 2000 encoder

More recently, the wavelet transform has gained widespread acceptance in signal processing in general and in image compression research in particular. Wavelet-based coding is more robust under transmission and decoding errors, and also facilitates progressive images transmission. Theoretically, the discrete wavelet transform (DWT) is a two dimensional separable filtering operation across rows and columns of input image. 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 four sub-bands as shown Figure 4: low-low (LL_1), low-high (LH_1), high-low (HL_1) and high-high (HH_1) [9]. 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

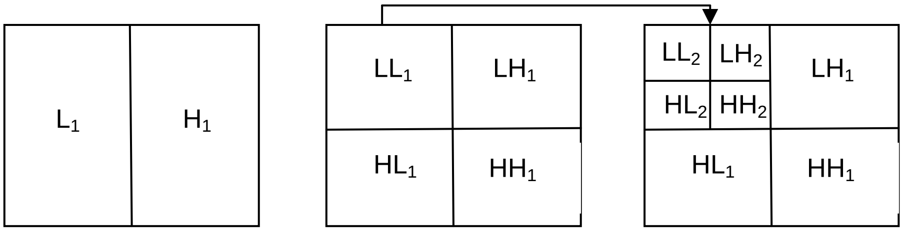

Figure 4. Illustration of wavelet spectral decomposition.

After the DWT, all the sub-bands are quantized to reduce the precision of the sub-bands. The quantized DWT coefficients are converted into sign-magnitude represented prior to entropy coding. In the embedded block coding method, each sub-band is divided into "code blocks". Then each code block is coded independently from the other ones thus producing an elementary embedded bit-stream. During the coding step, each code-block is decomposed into a number of bit-planes: One sign bit-plane and several magnitude bit-planes. The entropy coder for JPEG2000 uses embedded block coding with optimal truncation (EBCOT). EBCOT is divided into two coding steps: Tier-1 and Tier-2 coding. The first is based on tree pass: significance propagation pass (Pass1), magnitude refinement pass (pass2) and cleanup pass (pass3); the tier-2 is used to organize the portfolio among bit-streams from every block [10].

3. Research Method

Distributed image compression is proposed as a means to overcome the computation and energy limitation of individual nodes by distributing the processing of tasks. An example of distributed cluster- based compression is shown in Figure 5.

When applying the scenario proposed insection 3 and after receiving a query from a source node, the cluster head c_1 selects a set of nodes n_{1i} (i = 1…4) in the cluster which will take part in the distributed tasks then informs source node. 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 Figure 4(b)) to the next cluster head c_3. The cluster head c_3 chooses a part of the results (corresponding to LL_1 in Figure 4(b)) and distributes it to the set of nodes n_{3i} (n_{31}, n_{32}, n_{33} and n_{34}). Those nodes run 1D-DWT 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 Figure 4(c)) to the next cluster head c_4 for the quantization step. This procedure may continue on c_5 and its following nodes until the final compressed image reaches the destination node (sink). It should be noted that, as shown in Figure 6, after the DWT, all the sub-bands are quantized by a single node (n_{4i}). The other nods 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_5 divides quantized sub-bands into a number of smaller code-blocks of equal size and send their processed results to set of nodes n_{5i} (n_{51}, n_{52}, n_{53} and n_{54}). In these nodes each code-block is entropy encoded independently to produce compressed bitstreams.

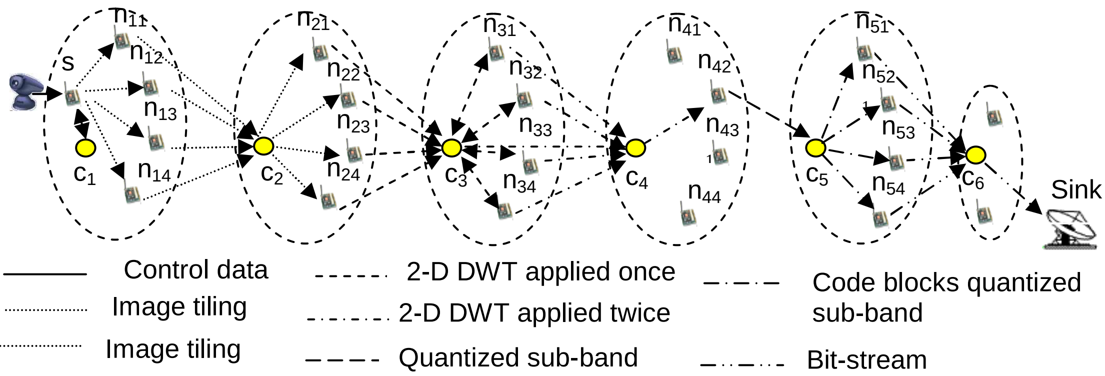

Figure 5. Data exchange of distributed task for image compression in a multi-hop wireless network. Two levels of wavelet decomposition are used

For this study, we have adopted the 9/7 DWT 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. In this case, each pixel is read and written twice. Assuming that the input image size is of M×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:

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

where S, A, R_{mem}, and W_{mem} represent the energy consumption for shift, add, read, and write of one-byte instructions, respectively [11].
The energy spent in entropy coding per bit is:

$$E_{ENT} = \delta \tag{2}$$

The image quality is measured by using the PSNR metric, which is defined (in decibels) by:

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

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

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

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

3. Results and Discussion

The energy concentration in the image by successive decomposition levels will allow decreasing the amount of information to be transferred over the wireless channel. 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. As a result, reducing the quantity of transmitted data will extend the overall lifetime of WSNs. From the experiment, an image Lena of size 256×256 pixels 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

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

The average energy dissipated by every node is provided in Figure 6. The energy consumed by the set of nodes n_{1i} and n_{2i}(i=1….4) to run 1D-DWT in horizontal and vertical direction respectively is of about 301mJ (by component) each one 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.

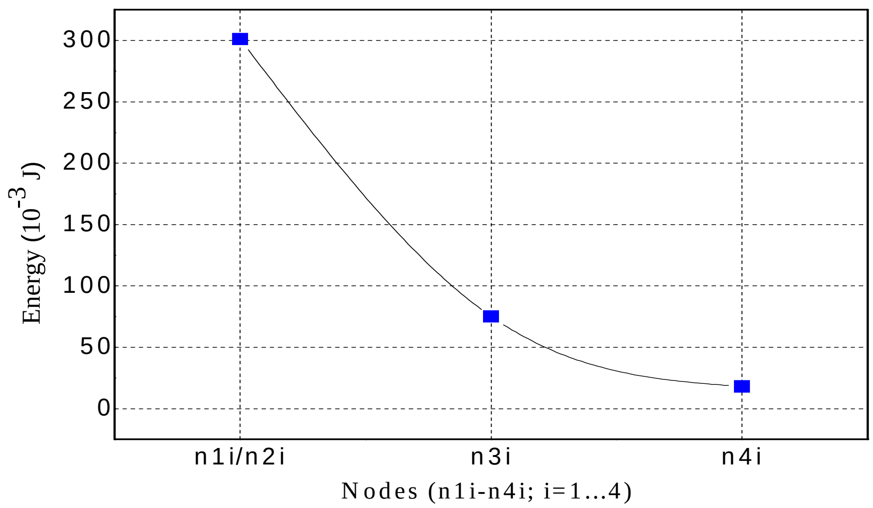

Figure 6. Computational energy dissipated by every node

In this case, we were interested by analyzing the impact of the decomposition levels on the enhancement of the execution time. In Figure 7, it's represented the execution time till five decomposition levels using the LS 9/7 DWT. We have considered Lena image with different dimensions. It is observed that 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_i sub-band. Therefore, an additional decomposition is useless and will waste energy without extracting more details. Figure 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 wavelet coefficients transmission from cluster head c_3 to the sink must be transmitted with priority in order to save more energy.

Coding a 32×32 LL sub-band with 4 magnitude bit planes when DWT is applied three, the energy dissipated is of about 5µJ (pass1) and 15µJ (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 10µJ each and the energy spent in pass3 is of about 2µJ. So decrease in magnitude bit planes leads to lower image quality (table1) and less computation energy.

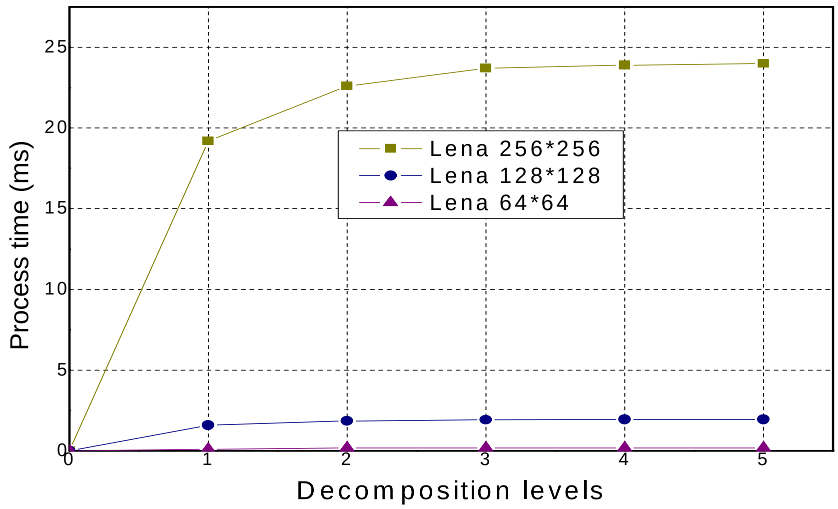

Figure 7. Process time for 5 decomposition levels of LS 9/7 DWT.

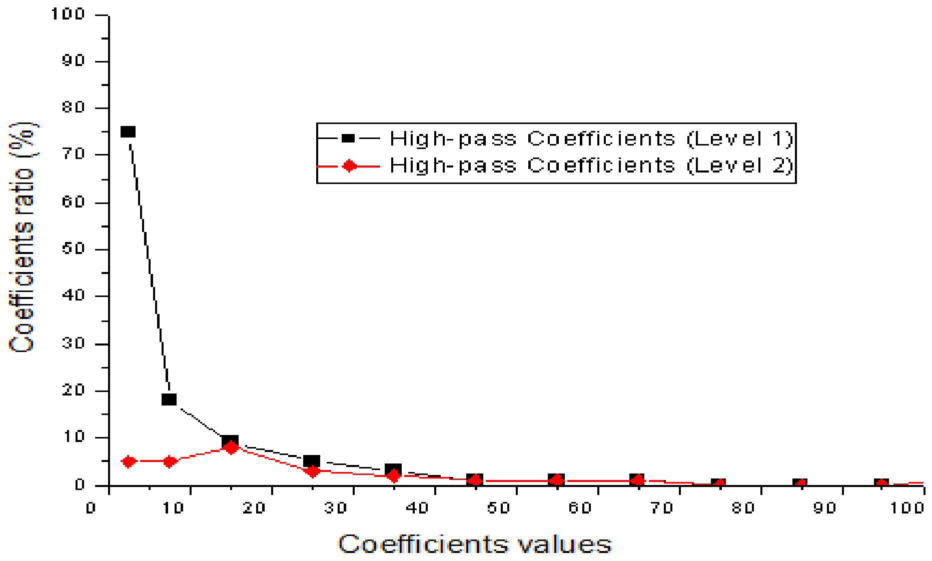

Figure 8. Distribution of high-pass coefficients

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.

Table 1. Measure basic element

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

4. 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, and minimize energy consumption. In addition, the adopted approach should minimize significantly computational energy of the nodes located next to the source (data is in an uncompressed form) by reducing the number of arithmetic operations and therefore, extends the overall network lifetime. The future research works must be focused on multipath routing which may enhance the performance of distributed image compression.

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