Experimental study of compressed images transmission through WSN

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Abstract—**With the rapid development of Wireless Sensor Networks (WSNs), the latter is increasingly getting used in critical environments. Multimedia networked applications have become more and more feasible over WSNs. The development of these types of applications requires extensive knowledge of multimedia network tools. For example, there is some research that presents constraints exactly to the use of wireless sensor networks for transporting multimedia applications such as image, video, etc. Image compression is one such technology that has been developed to reduce image size and used by WSN applications. In this paper, we describe a robust use of DWT and DCT image compression algorithm. Our performance evaluation shows that the DWT transform is better than the DCT in terms of image quality and execution time but the DCT outperforms DWT in terms of memory space used.**

Keywords-component: Wireless Sensors Networks (WSNs), Image compression, Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Computational complexity, Experimentation.

I. INTRODUCTION

WSN is a network composed of many nodes communicating among themselves and applied in a wide range of areas, such as military applications, public safety, medical applications, surveillance domain, environmental monitoring, commercial applications, habitat and tracking [1, 2, 3]. In general, sensor networks will be ubiquitous in the near future, since they support new opportunities for the interaction between humans and their physical world. Deploying sensor nodes in an unattended environment will give much more possibilities for the exploration of new applications in the real world [4].

A sensor node is a small device able to collect information through one or more sensors, to elaborate this information locally and to communicate it to a data collection center called base station. So, nodes are equipped with a processing unit with limited memory and energies resources and a communication unit, usually a radio transceiver. Nodes are powered by small batteries which generally cannot be changed. The application of multimedia (image, video, etc.) on wireless sensor networks is being, these days, a great requirement for the research and industrial community [5]. The current researches deal with image processing like data extraction, image processing and analysis [6].

The experimental approach has been proposed in other research works but with other method and for other purposes [7, 8, 9]. Compression image is one such technology that has been developed to reduce image size. This is why this method was adapted to the context of the wireless network that will catalyze applications such as: medical imaging, image databases and video-on-demand systems.

The objective of our work is to experimentally test two techniques for image compression to ensure that they are effective or not for image transmission through wireless sensor network. The two selected techniques are from two different families which are: discrete wavelet transforms (DWT) and discrete cosine transforms (DCT). The implementations of these methods on a real wireless sensor platform are allowed to reconcile with the real problems related to image processing applications.

Recently, Wireless Sensor Network [10] has been an active area of research and a wide range of applications have been developed. Sensor nodes are mainly characterized by their scarce resources and limited energy.

In the literature, most current research related to image compression in wireless sensor networks [11, 12] are limited to the evaluation by simulation. The authors have used several methods in the compression CWHN as LBT, SPIHT [13], ISEC [14] tested by simulation and tested on a real platform on Mica2. For instance, ISEC makes a compression method at the source, which uses a coding block of 2x2 pixels and removes one pixel from the 4 to minimize the compression rate and then finds the missing pixel using three present pixels. In [15], there is a comparison between two models of selection zonal coefficient of the DCT, one using a square shaped area and the other a triangular area.

In our work, a considerable effort has been given to compare two models for image compression to ensure they are effective or not for image transmission through wireless sensor network called DWT and DCT. Compared to other projects in WSN, this project focuses more on low-bitrate image transmission over long-range outdoor sensor networks.

The aim of our paper is as follow: Firstly, we compare two methods of compressing images which are the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT) and test their capability on wireless sensor networks (WSNs). Secondly, implement these methods on a real WSNs platform with TelosB sensor type. Thirdly, we execute performance evaluation and we compare the two methods in terms of image quality, execution and transmission time, packet lost and memory usage.

II. DCT AND DWT TRANSFORMS

In this section, we introduce the two transforms briefly, and outline their relevance to the implementation of compression algorithm:

A. *The DCT Transform*

Discrete cosine transforms is a technique used to converting a signal into elementary frequency components [16]. It represents an image as a sum of sinusoids of varied magnitudes and frequencies. In this step each block is transformed from the spatial domain to the frequency domain. This will generate a matrix of 8x8 frequency coefficients. After this transformation, most information in the block will be concentrated to a few low-frequency components.

The important problem in the image and video coding community is the size of image. To reduce it, an efficient algorithm for the DCT transform is desired; therefore they have been studied extensively.

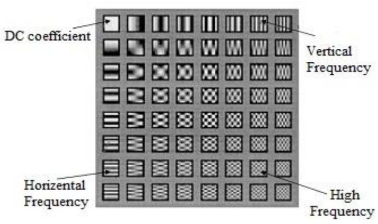

Figure 1. Basis vectors of 8x8 DCT

In this project a Fast Discrete Cosine Transform (FDCT) was used to minimize the execution time of compression algorithm. FDCT is an operation that applies to each block of size 8x8 and not the entire image which allows a high compression ratio. After decomposing the image into blocks and performing the processing of FDCT, we obtain a matrix whose components are the coefficients of the transform. Thus, we obtain two types of coefficients, DC and AC. The DC coefficient represents the first element of the transformed matrix, the remaining components are AC coefficients. Then, performing spot quantification, reorganization Zig-Zag and finally entropy coding.

B. *The DWT Transform*

Discrete Wavelet Transform is a mathematical transform that separates the data signal into fine-scale information known as detail coefficients, and rough-scale information known as approximate coefficients. Its major advantage is the multi-resolution representation and time-frequency localization property for signals. DWT has the capability to encode the finer resolution of the original time series with its hierarchical coefficients. Furthermore, DWT can be computed efficiently in linear time, which is important while dealing with large datasets [17]. Since image is typically a two-dimensional signal, a 2-D equivalent of the DWT is performed [18]. This is achieved by first applying the L and H filters 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 subbands, LL, LH, HL, and HH, as depicted in figure 2(a). The LL subband contains the low-pass information and the others contain high-pass information of horizontal, vertical and diagonal orientation. The LL subband provides a half-sized version of the input image which can be transformed again to have more levels of resolution. Figure 2(b) shows an image decomposed into two resolution levels.

Due to its excellent spatio-frequency localization properties, the DWT is very suitable to identify the areas in the host image. In particular, this property allows the exploitation of the masking effect of the human visual system such that if a DWT coefficient is modified, only the region corresponding to that coefficient will be modified. In general most of the image energy is concentrated at the lower frequency sub-bands LLx and therefore these sub-bands may degrade the image significantly. On the other hand, the high frequency sub-bands HHx include the edges and textures of the image and the human eye is not generally sensitive to changes in such sub-bands. So, data could be compressed to reduce the global amount of data to send.

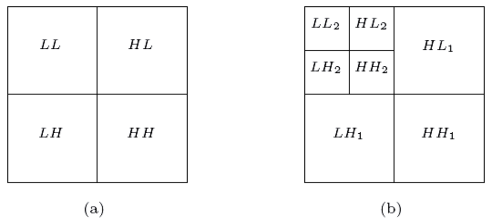

Figure 2. DWT applied one time (a) or two times (b)

III. PERFORMANCE EVALUATION

We evaluate our work on the real platform in terms of space complexity, time complexity and amount of information. The comparison will be very detailed depending on the results obtained through the PSNR curves taking into account studies on image quality, execution time, image resolution and memory used. In our experiment, we evaluate two compression techniques in image processing applications. We focus on the following question: Are these techniques valid for the context of WSNs? For there, we follow the steps of scenarios, measurement parameters and materials used that allow us to do our assessment.

The variants used in the scenarios is the case for which we used only two sensors that are used for intermediate nodes without any obstacles are: the number of packet lost either by the technique of DWT or DCT compared to the distance for an image 32x32 and 64x64, the evaluation function of the PSNR over the distance, the transmission time and memory used. And therefore viewed the images received for each technique used and the distance traveled.

We used TelosB motes with the TinyOS operating system to validate and measure the performance of our proposal. The TelosB motes have the following characteristics.

TABLE I. CHARACTERISTICS OF SENSORS NODES

Manufacturer	Processor	Program Memory	RAM
Crossbow	IT MSP430	48 KB	10 KB

Clock	Radio Unit	Band/Data rate	Max Consumption
8MHz	Chipcon CC2420	2.4 GHz / 250 kbps	1.8 mA

A. *The Process of the Algorithm Implementation usingDCT*

The compression of an image at the sensor node includes several steps. First, image is transformed into a format suitable for image compression. Each component of the image is then split into 8x8 blocks. The next step of encoding a block involves transformation of the block into the frequency plane. This is done by using a forward discrete cosine transform (FDCT). The reason for using this transform is to exploit spatial correlation between pixels. After the transformation, most of information is concentrated to a few low-frequency components.

To reduce the number of bits needed to represent the image, these components are then quantized. This step will lower the quality of the image by reducing the precision of the components. The tradeoff between quality and produced bits can be controlled by the quantization matrix, which will define the step size for each of the frequency component. The components will also be ZigZag scanned to put the most likely non-zero components first and the most likely zero components last in the bit-stream. The next step is entropy coding. We use a combination of variable length coding and Huffman encoding. Finally data packets are created suitable for transmission over the wireless sensor network.

This flowchart illustrates the coding scheme of the FDCT transforms:

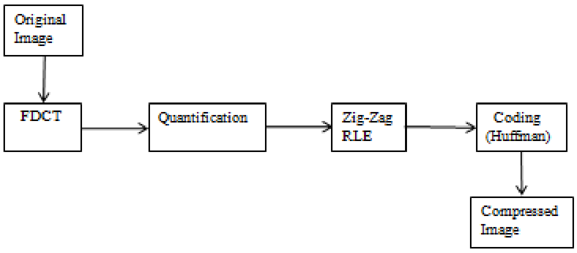

Figure 3. Coding Scheme of the Fast Discrete Cosine Transform

B. *The Process of Algorithm Implementation using DWT*

Then, for the second algorithm, the image is transformed into a suitable format to an image compression. The filters divide the input image into four non-overlapping multi-resolution sub-bands LL, LH, HL and HH on the first level. The sub-band LL represents the coarse-scale DWT coefficients while the sub-bands LH, HL and HH represent the fine-scale of DWT coefficients. Each subband contains the low-pass information and the others contain high-pass information of horizontal, vertical and diagonal orientation. The next step is quantification and coding of subbands used to reduce the number of bits needed to represent the image. This step will lower the quality of the image but not like DCT. The quality will depend on the value of the quantization used. The bit plane coding and subbands provides various coding modes, the compressed image can indeed be represented by increasing resolution or by increasing quality. The next step is arithmetic coding. It is a variable length coding. Unlike other encodings, it encodes the source message fully and represents a single number. Finally data packets are created suitable for transmission over the wireless sensor network.

The following figure shows the different steps of the DWT transform:

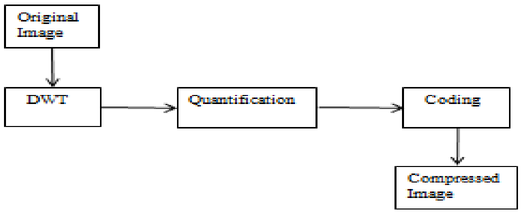

Figure 4. Coding Scheme of the Discrete Wavelet Transform

IV. COMPARATIVE STUDY BETWEEN THE TWO COMPRESSION TECHNIQUES

In this section, notes that all scenario are applied for DCT and DWT transforms.

A. *Packet Loss*

In this scenario, we have used 2 TelosB motes. Compression and decompression are performed respectively at the source and destination nodes. For radio communication, our implementation is based on 802.15.4 PHY and MAC layers which is a standard protocol for low-rate wireless personal area networks (LR-WPANs).

There are different images uses for experimentation, we choose for example Lena to do the different scenario.

Figure 5. Original Images

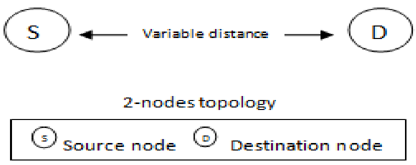

Figure 6. Example of transmission scenario

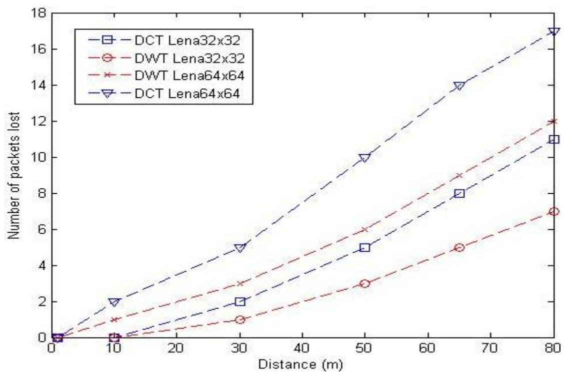

Figure 7. Lost packets vs distance between nodes

Figure 7 report the number of lost packet of DCT and DWT in different image size when transmitting compressed image. It show that the number of lost packet is not the same in DCT and DWT, so for Lena 32x32, it becomes clear from a distance of 12 m and 7m for Lena 64x64, then the greater the distance is, the more the packet lost will be. A packet is lost when retransmissions failed. This can explain why a better image quality is obtained with DWT compression.

B. PSNR

As a measure of the quality of image, the peak signal to noise ratio (PSNR) is typically used. This PSNR ratio expresses the difference in quality among the original Lena image and the decomposed one, while the higher the PSNR is, the better the quality of the decomposed image is. The expression of PSNR in decibels (dB) is given below in (1).

$$PSNR = 10\ \log_{10}\left(\frac{255^2}{MSE}\right) \qquad (1)$$

$$where:\quad MSE = \frac{1}{m\ n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\|I_0(i,j) - I_r(i,j)\right\|^2$$

$$m,n\ = image\ size > 0, I_0 = original\ value, I_r = compressed\ value$$

The following figure illustrates the obtained PSNR by varying nodes distance respectively for 32x32 and 64x64 images. According to these figures, images quality is better using DWT regardless of the distance and resolution. For distances higher than 30m, a higher gap of PSNR values is obtained. Quality is reduced when increasing distances between source and destination nodes.

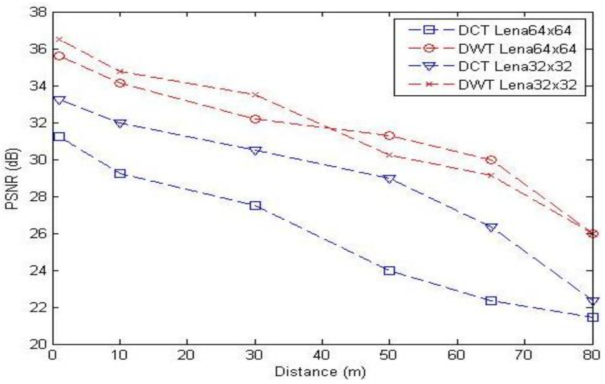

Figure 8. PSNR vs distance

The reconstructed images (Lena) for different distance (d) between sensor nodes are given by figure 9 and 10.

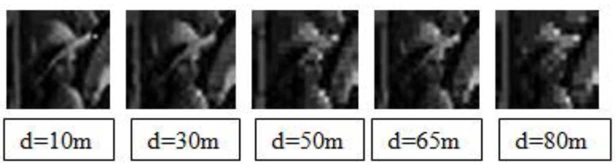

Figure 9. Obtained images with different distance for Lena 32x32

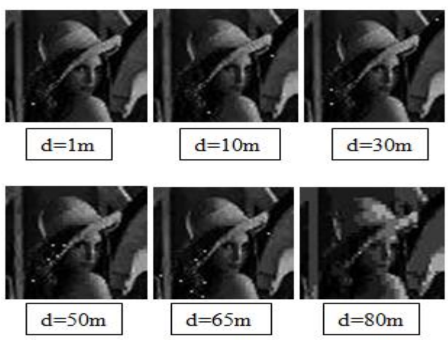

Figure 10. Obtained images with different distance for Lena 64x64

We conclude that the image quality decreases when the distance between the nodes increases. We show that at some distances we get blurred images that are due to packet loss. In addition, the image size has a great influence. For example, we found using different sizes of Lena images, that for Lena 32x32, the reconstructed image becomes blurred when the distance exceeds d = 30m and for Lena 64x64, the distance is d = 50m. There are white dots in the Lena 64x64 due to the complete loss of pixels that are replaced by the value of the white pixel.

C. Transmission Time

Figure 11 illustrate the end to end transmission time. We can also conclude that the DCT takes more time to be transmitted than the DWT for Lena image size 32x32 and 64x64. This is due to the block compression, radio transmission and decompression of this block. For the reconstructed of entire image, it is necessary that the number of packets sent are totally received. If a packet is lost, a retransmission of this packet is needed, which increases transmission time.
A question can be asked that why we used the Lena image with only two sizes are32x32 and 64x64 and not other sizes?
The answer is simple because it depend by the memory available by the sensors and consequently it affects the transmission time because the coding phase depend of the microcontroller used (hardware). We can of course use images size 128x128 and more, but the coding phase will be processed by the PC which it won us in terms of transmission time which is almost equal to 50%.

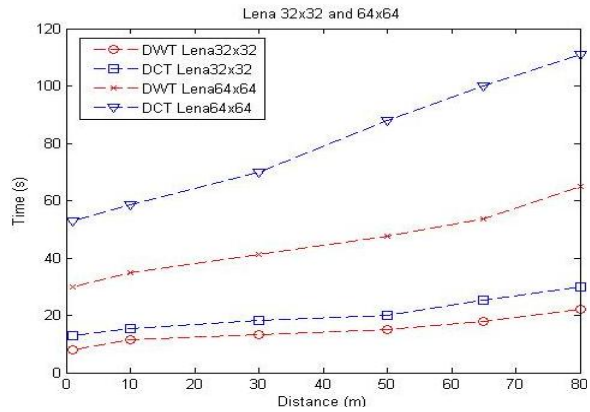

Figure 11. End-to-end transmission time vs distance

V. TRANSMISSION WITH AN INTERMEDIATE NODE

A. Testing Scenario

We are interested in this section to a topology with larger number of nodes. Our experiments were performed on TelosB wireless sensor nodes.

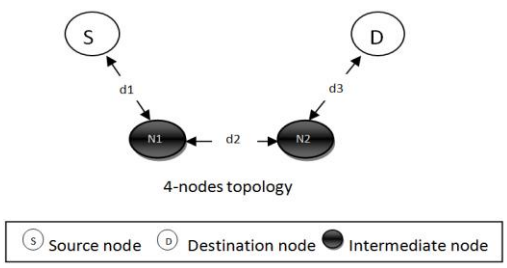

Figure 12. Transmission scenario with intermediate nodes.

This figure represents an image transmission scenario from source to destination node through node N1 and node N2. Compression and decompression are performed respectively at the source and destination nodes. Intermediate nodes only transmit compressed images. We used different image types and different resolution (32x32 and 64x64). We varied distance between source and destination nodes (d=d1+d2+d3). For each configuration, tests are performed with DCT and DWT. Measured parameters are the quality of reconstructed images (using PSNR), end to end transmission delays, packets loss rate and memory usage.

B. Packet Loss

Packet loss increases when using an intermediate node between source and destination nodes.

TABLE II. LOST PACKETS VS DISTANCE BETWEEN NODES FOR LENA64X64

Distance	d=30m	d=50m	d=65m
Lost Packets (DWT)	3	8	11
Lost Packets (DCT)	1	4	6

By comparing the results with Lena64x64 without intermediate nodes through which is shown in figure 7, we note that there is a gain in terms of lost packets because when you decrease the distance between the source and destination by one or more intermediate sensors, we decrease therefore the risk of losing packets. So, for distance d = 65m, there is a gain of 7 packets compared to the results without intermediate nodes.

C. PSNR

The PSNR with an intermediate node is shown in the following table. We notice that the PSNR decreases for higher distances.

TABLE III. PSNR VS DISTANCE WITH INTERMEDIATE NODES.

Distance	d=30m	d=50m	d=65m
PSNR(dB) DWT	34	32.26	30.19
PSNR(dB) DCT	26.65	26.67	24.48

It's clear from the table that for values of PSNR found without intermediate sensor, we note that there is an improvement in image quality. For example, for distance d = 30m, the PSNR of 27.23 dB has evolved to 29.65. So the greater the number of intermediate node, the more the image retains its quality. We also note that the curves punters have not changed much by changing the topology of two nodes one for the source and one for the destination to another compound of intermediate nodes, also the margins between the two curves DCT and DWT have not changed.

D. Transmission Time

In the following table, we draw the transmission time when using Lena64x64 with an intermediate node.

TABLE IV. TIME VS DISTANCE WITH INTERMEDIATE SENSORS.

Distance	d=30m	d=50m	d=65m
Time (s) DWT	41	56	68
Time (s) DCT	64	97	117

From this table, we can see that the transmission time in DCT is higher than the DWT. Compared with the topology with 2 nodes, the transmission time is greater than that containing intermediate node. This is due to the number of intermediate sensors added.

E. Obtained Images with an Intermediate Node

This figure shows the reconstructed images obtained with the use of intermediate sensors that are used across different distances. The first two images represent the images using DCT and the last two images are obtained by using the DWT technology.

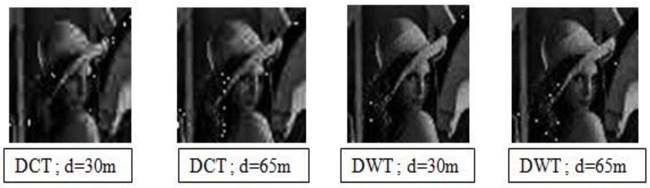

Figure 13. Obtained images with different distance for image 64x64

From this figure, we can conclude that the more we increase the distance, the more there is degradation. It is clear also that there is a difference between the images using DCT and DWT. In fact, the compression based on DWT gave better results in terms of image quality. The total number of packets for a 32x32 image is 16 and each packet contains 64 bytes (we increased the default size of the block of 29 bytes to 64 octets) in order to decrease the execution time in radio emission, and transmit the minimum number of packets in order to consume less energy...).

VI. EXECUTION TIME AND MEMORY USAGE

A. Evaluation of Execution Time

To evaluate the duration of execution time for each compression methods, we used the RunTime interface that are provided by the TinyOS platform for measuring the elapsed time between events and calculate the execution time of all the program of each treatment or separate module. Using the tools described above for different image formats (16x16 and 32x32 and 64x64), we obtained the results presented below:

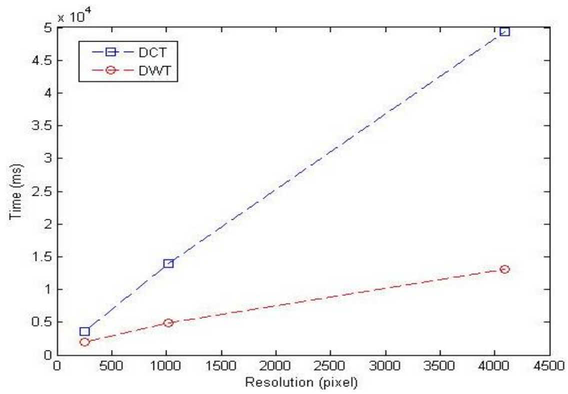

Figure 14. Evolutions of execution time according to the image resolution.

This difference in execution time between these two methods is due, in the case of DCT, to the decomposition of the image into 8x8 blocks which will be then compressed one by one, while in the case of DWT, image will be compressed at the same time allowing it to have a short running time as compared to the DCT.

From figure 14, we note that the length of image compression for the compression phase increases as the resolution of the image. However, the cost of a higher resolution is much higher for the DCT transform. It is found that the size of the image has no influence on the time complexity for the DWT transform, unlike the FDCT where the rate of change of the curve increases more rapidly by increasing the image resolution.

B. Memory Usage

The memory used in our application is the memory allocated to install the program and doing in parallel the intermediate computation. These measures in figure 15 are obtained by varying the image size.

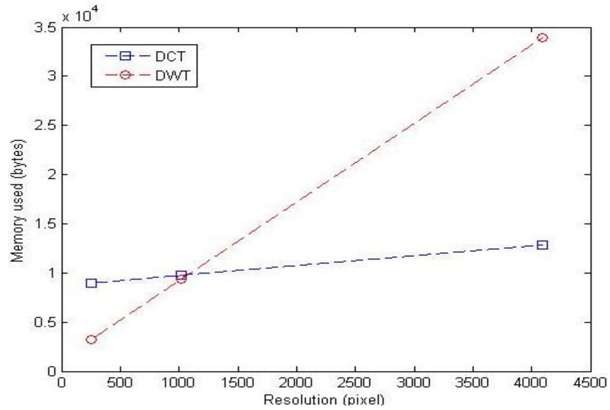

Figure 15. Memory space used.

Knowing that the hardware resources are limited by 10 KB of RAM and 48 KB of ROM, we are obliged to put their values into consideration while optimizing our algorithms and our treatment. We concluded from this figure, that when we increase the resolution the memory size increases rapidly for DWT more than DCT.

VII. CONCLUSION

Image compression algorithms which are based on the discrete wavelet transform have been widely recognized to be more prevalent than others. This is due to the wavelets' excellent spatial localization, frequency spread, and multi-resolution characteristics, which are similar to the theoretical models of the human visual system.

Traditional compression algorithms such as JPEG2000 and JPEG are very inefficient on most software platforms used in sensor networks, since they have limited resources. Basic reasons from this are the algorithm size, processors speed and memory access.

In this paper, our objective was to compare two techniques for image compression which are Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) in terms of image quality, execution time and memory overhead. These techniques have been implemented on a real platform composed of TelosB sensor. Our implementation has shown that DWT outperforms DCT in image quality and execution time but DCT consumes less memory.

As a future work, we aim to measure the consumed energy which requires in the experimental step particular methodologies. In addition, we aim to implement our proposal on dedicated platform for multimedia wireless sensor networks (MWSNs) such as Imote2.

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