A Dual Scheme for Compression and Restoration of Sequentially Transmitted Images over Wireless Sensor Networks

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Abstract: In this article a dual scheme for compression and restoration of sequentially transmitted images over Wireless Sensor Networks (WSN) is presented. Nowadays such image based applications have significantly increased and are characterized by the need to transfer high volumes of multimedia data while exhibiting real time synchronization. Depending on the type of wireless channel and communication protocol adopted, during data transfer, a considerable number of data packets may fail to reach the destination target, with a corresponding direct effect on the received image quality. This loss of valuable information until now has been addressed by retransmission quality of service schemes. However, this approach increases the energy consumption along with the probability of congestion occurrence due to the rise of traffic load. This article proposes a dual transmission scheme for multimedia networks that aims to decrease the overall traffic load introduced by the retransmission schemes, while performing image restoration resulting from lost data packets, at the receiver side. The proposed novel dual scheme is based on: a) the Quad Tree Decomposition (QTD) algorithm that is adopted for compression of e image data to be transmitted by clustering the image in sets of variable size and of similar type of color information, and b) on the fast image inpainting algorithm to restore the effect of the missing data packets by reconstructing its missing portions from the surrounding information.

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The overall proposed scheme has been applied in multiple experimental studies that prove its efficacy

Keywords: Wireless Sensor Networks; Quad Tree decomposition; Image Inpainting; Wireless Multimedia Sensor Networks.

1 Introduction

Recent technological advances have enabled the inexpensive development of sophisticated wireless sensor nodes which have the ability to perform sensing, processing, communication and actuation tasks. A typical sensor node of this kind is a small sized device which consists of one or more sensors, a data processor, a memory unit, a power supply, a transceiver and possibly an actuator [1-3].

A sensor node, in accordance with the sensing units that it incorporates, can measure electrical, mechanical, thermal, magnetic, biological, chemical or optical features of the physical phenomena taking place at its surroundings. Through the collaborative use of a large number of sensor nodes, a WSN is able to perform concurrent data acquisition of ambient conditions at various locations of interest spread over wide areas. This is the reason why WSNs, based on the sensing capabilities of their nodes, are nowadays used in an ever growing number of applications including surveillance and reconnaissance, environment and habitat monitoring, fire detection, inventory control, biological and biomedical applications, traffic control, agriculture, energy management, machine failure diagnosis, monitoring and handling of emergency situations, as well as battlefield monitoring and control [4-6].

In most cases, sensor nodes are deployed over wide areas and transmit data to a sink node, referred as the base station. In the most common scenarios, the distance between a source node and a destination node, or the base station, may exceed the range of the transmission capabilities of the transmitter. Therefore, relaying is required via intermediary sensor nodes. That is why sensor nodes not only collect, process and transmit the sensed data, but are also responsible for forwarding received data from other nodes of the network. Thus, the operation of a WSN is correlated with the transmission of large volumes of data.

However, most of the energy expenditure of a sensor node takes place during its wireless communication and decreases whilst sensing and data processing [7]. Thus, the presence of heavy traffic load within a WSN causes rapid depletion of a node's energy reserves, which are, by principle of design, limited. Moreover, the presence of increased traffic load raises the probability of congestion occurrence. High congestion causes the number of packet losses to increase. In order to prevent data recipients from losing valuable information due to failed transmissions, retransmissions can be activated. Nevertheless, data retransmissions result in a considerable increase to the traffic load and subsequently, the network's energy consumption and congestion.

Nowadays numerous novel applications have been developed for use in Wireless Multimedia Sensor Networks (WMSNs) [8]. These networks are actually WSNs equipped with sensor nodes capable of sensing, processing and transmitting multimedia data. In image based applications, the volumes of data that have to be transmitted are even greater than in most other applications of WSNs. Therefore, in such applications the need for data traffic constriction becomes even more evident. In order to compensate for errors and packet losses during data transmission in WMSNs, techniques improving the perceptual quality of the transmitted multimedia content are employed in the Transport and Application Layers of the network [9]. Such erroneous behavior is mainly attributed to multi-path fading and interference. Popular compensative techniques include Forward Error Correction (FEC) and Automatic Repeat Request (ARQ), which both induce limitations to the transmission and energy consumption efficiency of a WMSN. ARQ burdens the allocated bandwidth by requesting retransmission of lost data packets while the decoding complexity of FEC requires additional computational resources of a node in a WMSN, as it has to be built-in to the transport layer. In addition, multimedia content requires extended functionality of the application layer of the WMSN due to the nature of the transmitted data, especially concerning video streaming. Additional functionality includes application-specific source coding techniques and collaboration of network nodes for in-network multimedia processing.

This article proposes a novel scheme for transmitting multimedia content over a WSN by attempting to render invasive techniques to the transport and application layer obsolete. The proposed approach is experimentally applied to image transmission and is characterized by its simplicity, as it is network-independent and does not rely on node functionality enhancement. The proposed scheme comprises of two fundamental tasks, the first being the coding of the images to be transmitted by utilization of the QTD algorithm. QTD compresses the volume of image data by clustering the image in sets of variable size and of similar type of color information,which in turn leads to a significant reduction of the volume of transmitted data The second task performed is the application of a fast inpainting algorithm over the received images in order to restore, based on existing surrounding information, the damaged or missing image portions. The method aims to optimally compensate for the loss of information, caused by failed data transmissions, by circumvention of retransmissions, while retaining basic node functionality. The tasks described are applied by the transmitter and receiver base stations, which in principle are equipped with extended computational resources with respect to nodes of a WSN.

Although both QTD and inpainting algorithms are generally utilized for the coding and restoration of images, they have not been so far jointly applied in image based applications of WSNs. Thus, the novelty of the proposed scheme lies on the combined application of lightweight compression techniques and fast inpainting methods, in the sequential image transmission of images over WSNs, in order to achieve the reception of images having adequately good quality, with considerably reduced communication cost. Finally, it should be noted that according to the authors' of this article best knowledge, this is the first experimental application of an inpainting algorithm for image restoration in the field of WSNs.

The remainder of this article is organized as follows. In Section 2 the QTD method is described while in Section 3, the state of the art in inpainting algorithms is presented. In Section 4 a detailed description of the methods adopted in the proposed scheme is provided. The architecture of the proposed experimental system and corresponding results, that prove the efficacy of the proposed scheme, are presented in Section 5. Finally, Section 6 concludes the article.

2 Image Compression via Quad Tree Decomposition Method

Most image coding methods are based on techniques of image decomposition. Typically, a natural image consists of several regions that are attributed by local similarity and many others that have extensively varying content. Therefore, it is wise when coding such an image to allocate less data for homogeneous neighborhood decomposition and more data for areas containing edges and texture. In the proposed scheme, QTD is utilized. QTD is an image segmentation method generally used for hierarchical decomposition. The key behind hierarchical decomposition is to divide an image into sufficiently homogeneous areas, the levels of which can be compactly encoded. In the corresponding bibliography, there are several image compression algorithms, with the most popular being the Discrete Cosine Transform, Fractal compression and the Discrete Wavelet Transform. The aforementioned techniques tend to be mathematically complex, except from the QTD algorithm. QTD has been widely utilized not for its low–complexity but due to its powerful compression potential as well [10-11].

These attributes constitute the QTD to be an ideal candidate for application in image based compression applications over WMSNs. In these applications most images are stored in raster format. Hence, any access to a raster image is sequential, starting from the top left–most pixel and ending at the bottom right–most pixel. The QTD can be applied in two alternative approaches [11]. The first is the Bottom–Up decomposition, where each image is initially segmented into blocks of the minimum possible size. In sequel, every four adjacent blocks of equal size are joined together if the new joint block is homogeneous. The overall procedure is repeated until no other blocks can be merged. The second implementation approach is the Top–Down decomposition, where each image is initially divided into four blocks of equal size. Next, each of the newly generated blocks recursively splits into four new blocks if it is inhomogeneous and its size is greater than the minimum possible block size. In general, in terms of processing speed, the Top–Down QTD is considered to outperform Bottom–Up QTD for images which are either big or smooth while the latter performs better for images which have either small size or extensive textural features [11].

The image compression performed in this work, was based on the Top–Down QTD method. Thus, each image can be divided in half along both axes, all the way down to pixel level. This recursive subdividing of blocks allows for the image data to be organized into groups, in accordance with the neighboring blocks. Specifically, every subdivision exists as one of four neighboring blocks, which is actually comparable to having a tree–like structure, where the root of the tree is the entire image recursively divaricating into four branches, until its leaves are pixels. In this manner, a quad tree is a tree with nodes which are either leaves (pixels) or have four children. As a result, each block is either completely a single color block or consists of four smaller sub–blocks. An example of a product of a QTD process is presented in Fig. 1.

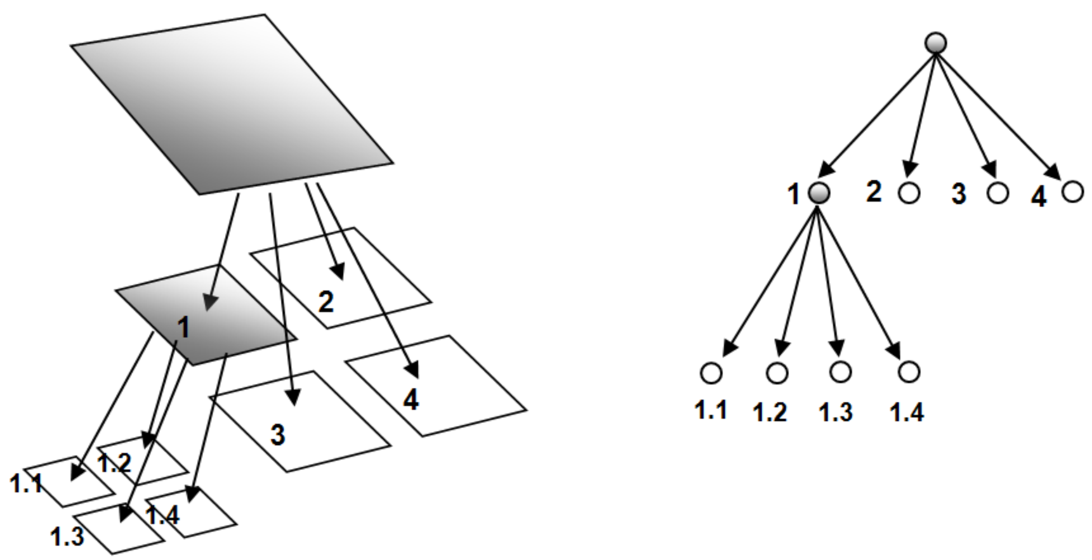

Fig. 1 QTD example in the form of a multilayer set of blocks and a corresponding tree structure

The tree like evaluation of an image enables the removal of the unnecessary leaves and branches of the tree, which result in the reduction of the QTD representation size. This could be achieved by checking every individual block against a criterion of homogeneity. In case this criterion is satisfied, the corresponding block is not divided any further. However, if the homogeneity criterion is not satisfied, the block is further divided into another four blocks. The process is executed iteratively until each block satisfies the homogeneity criterion [12-13], expressed as:

$$\max(MX_4 - AVG_4, AVG_4 - MN_4) \leq \frac{R}{L}\left(\frac{AVG_4{}^{(1-\frac{\gamma}{2})}}{q}\right) \qquad (1)$$

In this formula, MX_4 represents the maximum value of the four leaves of a branch, while MN_4 expresses the minimum value found on this branch, and AVG_4 symbolizes the linear average of the values found on this specific branch. At the right part of Eq.(1), which represents the threshold for removing the branches, R is the decomposition factor, expressing the degree of compression. Parameter L refers to a scaling factor which corresponds to the size of image region. For instance, L is equal to 1 for simple pixels 2 for regions of size 2 x 2s and so on. Moreover, γ represents gamma correction. Finally, q denotes the ratio of the region to image size. For instance, when γ gets the commonly used value 2 and q is equal to 128, the quantity inside the parenthesis simplifies to 1/128. Thus, for a pixel array derived from an image of size 256 x 256, it represents 1/128 of the image size. This means that there are 128 pixel arrays in a 256 x 256 sized image. If a leaf is removed, a quadrant will be represented by the average of the pixels it contained prior to pruning. The adoption of the homogeneity criterion expressed by Eq.(1), leads to the formation of images of reduced size created through QTD, similar to the QTD partitioned image illustrated in Fig. 2.

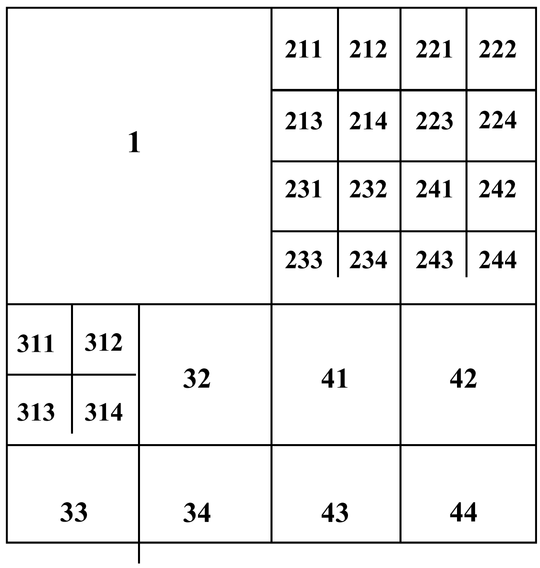

Fig. 2 Example of an image formation through QTD based on the homogeneity criterion

3 Image restoration through inpainting techniques

Various methods have been proposed for restoring and reconstructing images. The two most popular categories of these methods are namely texture synthesis and image inpainting. Image inpainting is the process of modifying an image by reconstructing its damaged or missing portions. Such techniques have been applied manually for centuries while popular texture synthesis techniques aim to reproduce large areas of missing pixels from images by extracting statistical features from textures. In this way, texture synthesis algorithms are able to repair textured regions of an image with high quality. However, this is not the case when dealing with regions containing structural information.

The approach proposed in this article focuses on preserving structural image information, since this kind of information is of greater importance in WSN applications, where recovering packet losses resulting from image transmission requires a more subtle and natural approach. Thus, the image restoration process is based on a variation of the original inpainting algorithm.

Nowadays, there are a wide range of algorithms developed for digital image inpainting, which at some extent replicate the basic techniques used by restorers. The main differences concern mathematical foundation, quality of results, topology dependence, speed of execution and the type of application. Until now, the most popular inpainting algorithms were based on: a) isophotes for joining points of equal light [14-15] b) Euler-Lagrange equation along with anisotropic diffusion (Total Variational) [16], c) Curvature–Driven Diffusion [17], d) partial differential equations (PDEs) [18-19], e) edge identification [20], f) global approach deriving from the global heat principle and its laws [21].

Recently the results from [18] have been extended in [22] by deriving a third order PDE that performs inpainting. The inpainting problem in this work is perceived as a case of image interpolation and level lines are propagated by expression in terms of local neighborhoods. Using the Taylor expansion, a third order PDE is derived, which optimally ensures the continuation of level lines. The method outperforms previous work in terms of both accuracy and contrast invariance. However, the execution of the algorithm is more time consuming.

An alternative and faster approach has been presented in [23], where the authors have proposed a method that incorporates the inpainting approach for completing missing regions in video sequences of complex dynamic scenes. Completion is achieved by an optimization of a global visual coherence function. The method fills in missing regions of the video sequence by using similar space–time patches extrapolated by the video sequence. In order to measure similarity among space–time patches the Sum of Squared Differences measure is adopted and applied to space–time points that are characterized by the RGB color coefficients and vertical as well as horizontal motion coefficients,thus comprising a 5-D representation for each point. To further optimize the algorithm a confidence measure is incorporated and the iterative process performs in multiple scales using spatio–temporal pyramids. The proposed method performs impressively for video–completion and can also be adapted to image completion by eliminating the temporal extent. The algorithm has been incorporated in the presented work as it outfits the need of a fast restoration scheme, for sequential images transmitted over a WSN.

The procedure proposed in this article for the image inpainting of the transmitted over WSNs compressed images is based on a fusion of the aforementioned methods proposed by Bertalmio [18] and Wexler [23]. It aims at the achievement of high quality of restoration along with high speed of execution. More specifically, the use of the PDEs [17] aids in preserving the image's structural information while the global visual coherence optimization defined in [23] prevents solutions with local inconsistency to be selected as viable candidates.

Let $I_0(i,j)$ be our discrete gray level image and Ω the region to be inpainted, where (i,j) are the pixel coordinates. As the algorithm execution progresses, a sequence of images $I(i,j,n)$, where $I(i,j,0) = I_0(i,j)$ and $lim_{n\to\infty}I(i,j,n) = I_R(i,j)$, are produced at each iteration n. This procedure ultimately results at the final inpainted image $I_R(i,j)$. At any step of its execution the algorithm can be generally described by

$$I^{n+1}(i,j) = I^n(i,j) + \Delta t I_t^n(i,j), \forall (i,j) \in \Omega \quad (2)$$

where n corresponds to the current step of execution, Δt denotes the rate of improvement and $I_t^n(i,j)$ represents the update at each step.

Let $\partial\Omega$ denote the boundary of the region to be inpainted. The goal of the proposed approach is to smoothly propagate the missing information into Ω. In order to achieve the above, the propagation direction $\vec{N}^n(i,j)$ and the information to be propagated $L^n(i,j)$ must be computed. These two coefficients define $I_t^n(i,j)$ as:

$$I_t^n(i,j) = \overrightarrow{\delta L^n}(i,j) \cdot \vec{N}^n(i,j) \quad (3)$$

where $\overrightarrow{\delta L^n}(i,j)$ denotes a measure of change in the information $L^n(i,j)$.

In order to achieve smoothness in the resulting image, which statistically balances the pixel intensity over a given region providing a more visually coherent result to a simple implementation of the discrete Laplacian is used for $L^n(i,j)$:

$$L^n(i,j) = I_{xx}^n(i,j) + I_{yy}^n(i,j) \tag{4}$$

The discrete Laplacian in (4) is incorporated to smooth the resulting image as the reconstructed region, if not manipulated as such, will present sharpness, especially around the area of the boundary pixels of the missing region. Smoothness statistically balances the pixel intensity over a given region and provides results which are not perceptually visible.

For the direction coefficient $\vec{N}^n(i,j)$, the direction of the smallest spatial change $\nabla^{\perp} I^n(i,j)$ is used as proposed in [18].In addition to the procedure described above an anisotropic diffusion technique is iteratively applied at every few steps of the execution of the inpainting algorithm to ensure the correct evolution of the direction coefficient. Anisotropic diffusion reduces noise in the applied region. As the in-painting algorithm progresses, driving towards the inner area of a missing region, the noise introduced increases as less original information are available for the specific area, resulting in deviance of the direction coefficient. Such information is propagated from the reconstructed pixels in a inwards approach and requires noise reduction in order to retain the algorithm efficiency unaffected or in these cases, less affected.

The discrete 2D anisotropic diffusion utilized in the proposed algorithm incorporates a 3x3 pixel neighborhood to contribute information and is described by:

$$I(i,j,t+\Delta t) = I(i,j,t) + \Delta t \cdot \begin{bmatrix} \sum_{k=-1,k\neq 0}^{1} I(x+k,y,t) + I(x,y+k,t) + \\ + \frac{\sqrt{2}}{2}\left(I(x-1,y-1,t) + I(x-1,y+1,t) + I(x+1,y-1,t) + I(x-1,y+1,t)\right) \end{bmatrix} \tag{5}$$

In order to increase the execution speed of the digital inpainting algorithm a multi-scale resolution approach is adopted. An iterative process over multiple scales is implemented. Each level contains ¼th of the pixels of the higher scale image, which is also the case for the missing region Ω.

The iterative process begins at the lower scale applying the inpainting algorithm. As the execution progresses, the direction of $\vec{N}^n(i,j)$ is propagated to the next level along with an estimation of $L^n(i,j)$ which acts as an initialization for the missing pixels of the image, resulting in a faster convergence of the algorithm. The algorithm is executed given the depth N of the multi-scale resolution and a maximum of M iterations of the inpainting algorithm. Moreover, the global visual coherence optimization proposed by Wexler [23] is incorporated to determine algorithm convergence and the SSD of the color (or gray-level) information is adopted to measure the change of information in the image from step I^n to I^{n+1}. If the result is below a predefined threshold, the inpainting algorithm completes its execution providing the output to higher execution level until the initial resolution is reached. In the proposed scheme: a) the advantages of the original inpainting algorithm with respect to information propagation are maintained, b) a global metric is adopted for quality measurement, and c) convergence is achieved rapidly by applying a multi–scale resolution scheme, which makes the method ideal for near real-time performance, a factor that is of paramount importance when dealing with image based applications over WSNs.

The overall proposed congestion-aware control scheme is illustrated in Fig. 3. In this figure it is shown that the images captured from a camera are coded according to QTD prior to being transmitted over the WSN. The selection of the acquiring source (digital camera or digital video equipment) and the image acquisition settings are of paramount importance for the overall application. Images of higher analysis will require greater transmission times, while images of low analysis, will speed up the transmission scheme but will reduce significantly the quality of the reconstructed images. Thus for every application, a compensation should be made among transmission time and reconstructed image quality. At the receiver side, the streamed data packets received are Quad Tree composed. The QTD algorithm for the decomposition and the reconstruction of the transmitted images, can be implemented in the node level by attaching the WSN-node to a microcontroller or to an embedded pc. Due to probable losses of data packets, which contain information for specific areas of the images transmitted, the received images may contain black-colored areas. In these cases, black-colored areas are identified through a masking operation on the received image and the inpainting algorithm for image restoration is applied in order to restore the missing areas.

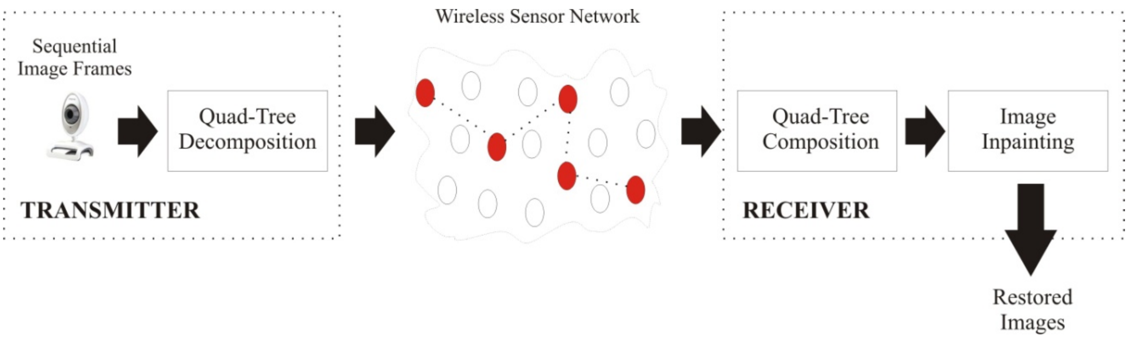

Fig. 3 Overall System Architecture for the reconfigurable transmission of images over a congested WSN

4 Experimental results

For the experimental verification of the proposed scheme a Zigbee–WSN has been established, consisting of one coordinator node, three routers and one end device. The coordinator is responsible for establishing the WSN network and transmitting the decomposed images as data packets to the Zigbee network [24-26]. Moreover, the routers are responsible for establishing connections within the WSN network in order to forward the decomposed image data packets (forwarders). The end device acts as the interface of the network to the computer at the receiver side. Finally, the image inpainting algorithm has been also executed on this computer.

For the presented experimental results, the benchmark image of an 8–bit gray scale image of Lenna with an analysis of 256x256 pixels has been selected. This image has been also utilized to produce sequential transmitted images, in order to simplify the reader's comprehension towards the variations in the quality of the received image, based on different QTDs, without a loss of the generality for the presented approach.

The test scenarios include the application of different decomposition factors on the same image and the sequential examination of: a) the effect of the packet losses on the same image, and b) the capabilities of the image inpainting algorithm. The network coordinator that is presented in Fig. 4 was constructed using a MaxStream XBee XB24BZigbee Modem [27] with a XBEE USB connector board from Sparkfun.

Fig. 4. The designed and implemented coordinator node of the utilized WSN

The XBee modem for the coordinator, routers and end device, were set up using the provided XBee API communication framework. The communication between the XBee modem and the computer were setup to a Baudrate of 9600kbps using hardware flow control on the serial port. The selection of this data rate has been made again without loss of generality, as the presented experimental results can be also be applied to higher Baudrates. In addition, the router devices do not require any wired communication interface, thus requiring only a power connection to be provided. The parameters that have been utilized in the WSN for our test case are outlined in Table I.

Table I Configuration of the utilized experimental WSN

Network Characteristics	Values
Number of Nodes (*N*)	5
Coverage Area (*M* x *M*)	20 x 20
Maximum Transmission Range (*m*)	40
MAC Sub-Layer Protocol	IEEE 802.15.4
Routing Protocol	ZIGBEE
Data size per Packet (*B*)	68
Data Size per Packet (Including Overhead) (*B*)	84
Transmission Interval (*sec*)	2.5
Distance Between nodes (*m*)	5
Interface Baundrate (*Kbps*)	9600
Interface flow control	Hardware (CTS/RTS)
RF Data rate (*Kbps*)	250
Transmit output power (*mW*)	1.25

The experiments were performed in the following sequence: First, the 256x256 sized image of Lenna of 8-bit color depth was decomposed to its Quad–Tree equivalent with a various decomposition factors, varying from 0.1 to 0.8 with a 0.1 discrete step and in sequel the image was transmitted over the network. Initially, all nodes were placed in a small area in order to avoid packet losses and to measure the time overhead for each QT-decomposition and transmission over the WSN. The effect of the decomposition factor on the quality of the original gray scale image of Lenna is depicted in Fig. 5. Additionally, in Fig. 6 the mean value of the experimentally measured overhead time elapsed from the initiation of the QTD process for an image until the reception of the full image at the receiver side is presented. For these measurements it should be noted that the calculations of the mean time value refer to sets containing 10 images of Lenna each and by using the same compression rate.

In Fig. 5 the top right image is the original Lenna image while the following ones are the images received with an increasing decomposition factor from 0.1-0.8 (e.g. The bottom right image of Lenna has been under QTD with a 0.8 decomposition factor).

Fig. 5 Decomposed image of Lenna for various QTD Factors

As it can be observed from Fig. 6, an average time interval of approximately 145secs was needed for the original Lenna image to undergo QTD and be transmitted via the WSN, which constitutes a time delay frame, although the network was utilizing its full bandwidth (only one active transmission of image in the WSN). From an application standpoint, when is the need to receive just one snapshot of an image with high quality is exhibited, such large delays are acceptable. On the contrary, when there is demand for sequential images of a scene (e.g. surveillance applications) such delays are mandatory to be highly reduced, which in turn results in a corresponding decrease of the quality of the received images. For example, if the selection of the QTD factor was equal to 0.5 (the second image of Lenna from the left on the second line in Fig. 4) then the end-to-end delay (from QTD until reception) would be 13.88sec.

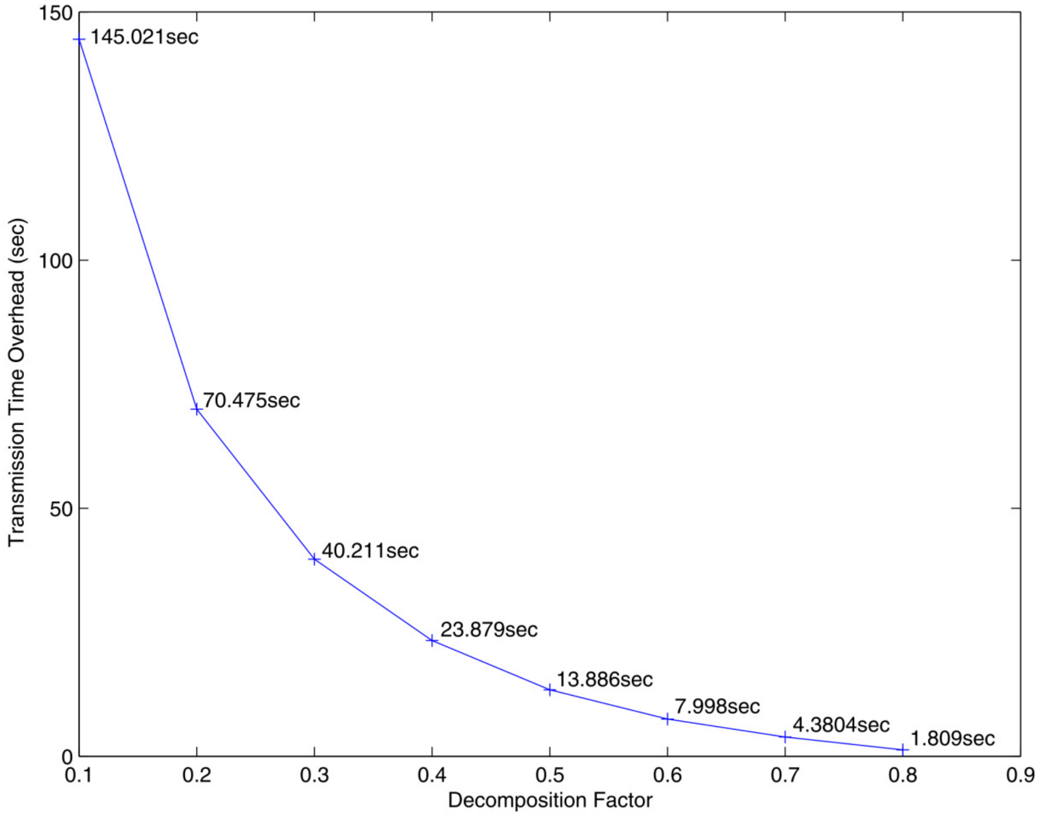

Fig. 6 Decomposition Factor vs. Time Overhead

In the case of utilizing such a QTD scheme with an appropriate decomposition factor, the received images will contain less blocks of valuable image data, and this is a straightforward consequence of the way that the Quad Tree decomposes an image. This means that, in case of a lossy transmission scheme, the effect of the missing packets on the quality of the received image will be dependant to the QTD factor. The higher the factor, the greater the effect of the missing image block will be. In order to improve the quality of the received images, even in the case of lost data blocks, our approach prevents the receiver from requesting retransmission of lost packets. Instead, the receiver base station performs image inpainting to indirectly retrieve the missing information from the received image. The execution of the fast image inpainting algorithm, presented in Section 3, as it is presented in what follows, consumes almost 2sec and it is evident that the request for retransmission of the lost data packets is outperformed in with respect to speed.

As an example, consider an application where the QTD factor has been set equal to L=0.5 (right side of Fig. 6) and again the goal is to transmit over the WSN, sequential frames of the original Lenna 256x256 pixels gray scale and 8–bit image. This time, the WSN nodes have been placed in an area of $20x20m^2$, where loss of data packets can occur. After the transmission of the QTD coded image, the lossy received image is decoded. Decoded images are presented on the middle portion of Fig. 7. This image has been checked for missing partitions and these missing blocks have been masked in red color (Fig. 7). The resulting image after the application of the inpainting algorithm is presented on the right side of Fig. 7. It should be also noted that for this experiment, the measured end-to-end delay has been 14.103sec.

The utilized inpainting algorithm would commence the repair process using an iterative multi–resolution approach. For each lower level the image was down–scaled to half the size of the level above and the inpainting algorithm was applied to the image frame. At each level the algorithm iterates by progressively filling in the missing pixels of the masked region by iteratively applying a maximum of N steps of inpainting Eq.(2) and diffusion Eq.(5) every M steps until convergence is achieved.

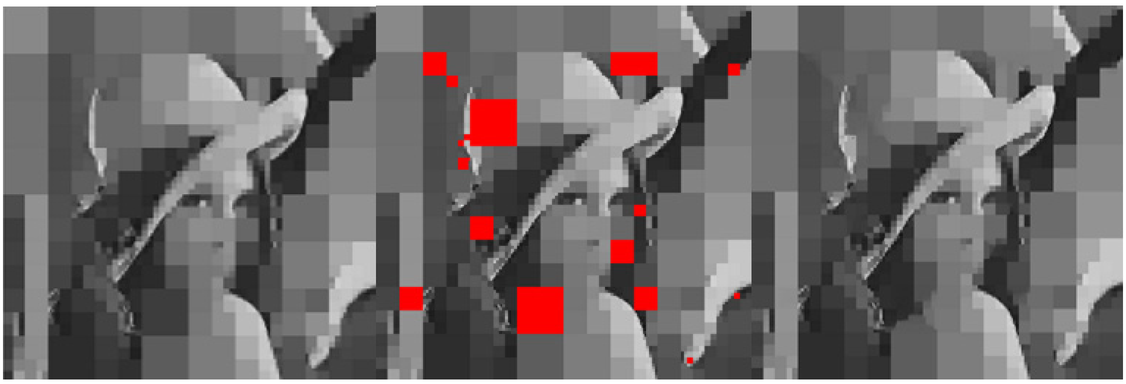

Fig. 7 The L=0.5 QT-decomposed image (left side), the masked received lossy image (middle portion) and the resulting repaired image(0.7 sec) 4–levels, $N=12$ (right side)

In Fig. 8, the second Quad–Tree decomposed frame of Lenna, with a compression factor of $L = 0.3$ (left side) and the received (19.8sec) masked lossy frame (middle portion) is presented. Finally, the results of the inpainting algorithm are also displayed in the same figure (right side).

Fig. 8 The L=0.3 QT-decomposed image (left side), the masked received lossy image (middle portion) and the resulting repaired image 4–levels(1.2 sec), $N = 12$ (right side)

From the experiments above it is obvious that the image inpainting algorithm achieves to reconstruct the missing informationfor all selected QT–decomposition factors. Smaller decomposition factors result in smoother restorations of missing partitions while more complex decompositions result in rougher restorations. This observation was expected, as the image inpainting algorithm bases its operation on the information surrounding a missing partition and there is no capability of increasing the level of detail in the reconstructions further than the provided quality of the image frame.

6 Conclusions

In this article a dual scheme for compression and restoration of sequentially transmitted images over Wireless Sensor Networks (WSN) has been presented. The proposed novel dual scheme is based on: a) the Quad–Tree Decomposition that compresses the volume of the image data to be transmitted by clustering the image in sets of variable size and of similar type of color information, and b) on the fast image inpainting algorithm to restore the effect of the missing data packets by reconstructing its damaged or missing portions from the surrounding information. The overall proposed scheme has been applied in multiple experimental studies that prove the efficacy of the proposed algorithm. Future studies will focus on the development of an adaptive scheme for: a) adapting the decomposition factor based on the current traffic load (round trip latency time) and b) utilizing the inpainting algorithm as it has been presented in this article.

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