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Image Compression and Wireless Multimedia Sensor Networks – A Survey

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Abstract

Objectives: Wireless Multimedia Sensor Network (WMSN) is a fast emerging technology, which can deal with audio, image and video along with scalar data. WMSN is widely used for many applications like wildlife monitoring, medical imaging and surveillance. The survey is to investigate the several image compression methods that are intended for WMSN. **Methods:** Compression techniques are used to minimize the volume of data transmitted, which in turn reduces the sum of communication power and processing power. Any operation performed on multimedia data should be lightweight and so traditional image compression techniques are not suitable. This mandates the growth of new techniques or modification of existing methods to make them suitable for WMSN. **Findings:** Suitability of the methods is analyzed by the metrics like compression efficiency, processing speed, memory requirement, power consumption, computational load and system complexity. It is found that SPIHT is the most suitable with limitations of moderate memory usage. Distributed Source Coding and Compressive sensing are in the developmental stage and will influence the future vision of image compression in WMSN. **Applications:** Every method has its own merits and demerits. The one to be chosen is entirely dependent on the application or user needs, the hardware/software platforms used for implementation and the cost constraints. The most desirable algorithm can be chosen and enhancements can be done as per the demands.

Keywords: Image Compression Algorithms, Memory Requirement, Power Consumption, Wireless Multimedia Sensor Network

1. Introduction

WMSN is used for gathering data in large scale and are increasingly used for continuous monitoring and controlling applications[1]. The picture is more worth than a word. Hence, instead of getting the sensor data alone, the actual situation can be understood more easily by means of an image. The growing technologies in miniaturizing the hardware devices used to capture multimedia data and the improvement in the Internet usage have led to the use of distributed digital imaging applications, based on networked devices. The sensor nodes are usually installed in huge quantity and are dispersed in unattended environments. Such tiny devices have resource constraints like finite power supply, limited communication bandwidth, processing speed and memory. The practical challenges in the design and development of such systems include the bandwidth availability to deliver huge amount of multimedia data, the development of multimedia processing methods and the ability to secure such data during transmission[2]. These constraints motivate the need for the development of approaches that can reduce the volume of data without altering its semantics, with less communication overhead and complexity. Power consumption is the major constraint to be considered in WMSN as it affects the maximum operational lifetime of the network. The major constituents of power consumption in sensor networks include the sensing, processing and transmitting power. It is well known that the transmitting power is the highest among all. By compression techniques the transmission power can be reduced with a minimal increase in the processing power. The primary building blocks of the image are pixels that are highly correlated in nature. The goal of coding or compression is decreasing amount of data by removing redundancy without affecting the

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original information. Redundancy in the image is usually classified as three types[3].

- Inter-pixel or Spatial or Inter-frame or Geometric Redundancy: Image contains pixels that are correlated i.e. there will be larger regions in which the values of pixels are almost the same. The compression techniques used to remove this type redundancy includes Constant Area Coding (CAC), Run Length Encoding (RLE) and Predictive Coding.
- Coding or Temporal Redundancy: It is due to the association between the contiguous frames in system of images. Deals with reducing the amount of bits required for image representation. The encoding technique is usually grounded on Look up tables and the commonly used techniques are Huffman and Arithmetic coding.
- Psycho-visual or Spectral Redundancy: This type of redundancy is due to the correlation between the colour planes. It is removed by reducing the quality of image without affecting the human perception to a greater extent. The commonly used coding algorithms are cosine and wavelet transform which incorporates quantization as one of the steps of image compression.

2. Performance Metrics for Image Compression

The performance of an image compression method can be analyzed by using some of the metrics like measuring the distortion in the reconstructed image, the compression ratio obtained and the time and power consumed for the process[4]. The level of tolerance to these parameters is determined by the application.

2.1 Image Quality Evaluation

Assessing the quality is mainly focused on determining the variation between the original and recreated image in terms of distortion between the two. Minimal amount of distortion means the better quality of image. Some of the commonly used techniques are explained:

- Mean Square Error (MSE): It calculates the average of all the squared differences among input and recreated image sequence.
- Peak Signal to Noise Ratio (PSNR): It indicates the amount of unwanted signal present in the original signal. The maximum value for 8-bit pixels is given by 255.
- Structural Similarity (SSIM): It is a reference index to know the visual deprivation of recreated image from basic image[5]. This model is developed to remove the inconsistencies of visual perception in the traditional methods of MSE and PSNR.

2.2 Compression Ratio (CR)

CR gives the reduction in size of image data representation. Compression ratio is obtained by the proportion of the quantity of bits in recreated image and in input image. Higher the compression ratio more is the quality loss of the reconstructed image.

2.3 Compression Time

The speed of compression depends on the algorithm used and computational resources of the platform. Though lossy compression technique is efficient the speed of execution is influenced by the storage space, complexity and the computational load. For WMSN the algorithm should take lesser time and should use minimal resources of the node.

2.4 Power Consumption

Compression technique should aim at minimizing the total of processing and communication power. Hence, while choosing the algorithm care should be taken about the trade-offs among processing complexity, data reduction and power consumption.

3. Categories of Image Compression

Compression procedures for image can be widely categorized as lossy and lossless. Both have their own advantages and drawbacks. Lossless method reproduces the original image quality. Lossy technique has its benefits like lesser processing time, higher compression ratio and lesser energy consumption than the lossless method.

3.1 Lossless Compression

If the process of redundancy removal is completely reversible without any loss of data, it is termed as lossless compression technique. This method is usually applied as a two-step process[6] viz. 1. De-correlation and 2. Entropy coding as shown in Figure 1.

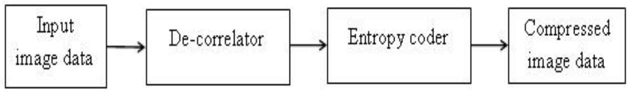

Figure 1. Lossless image compression.

3.1.1 De-correlation

De-correlation is performed as a first step, which is nothing but the removal of spatial redundancy among the pixels by lossless method. It can be done in any of the ways described as follows:

- Prediction of the pixel values based on the already available information[7]. All the pixels are represented by a prediction error with respect to the neighboring pixel.
- Transform based method[8] uses lossless transformation of image from spatial to frequency domain and the converted factors are given as input to the next stage.
- Multi-resolution based method[9] splits the image into multiple components. Lower frequency components that represent much of the needed data are transmitted first and the higher frequency components are transmitted progressively.

3.1.2 Entropy Coding

Entropy encoder is the actual compression step in the lossless method. This step removes the coding redundancy of the image. The popular encoders of this type are:

- Huffman coding uses the probability distribution of the image symbols[10]. It represents the symbols with variable length codes, shorter code for highly repeated symbols and longer code for less repeated symbols.
- Arithmetic coding encodes the whole message with a single numerical representation. This achieved by dividing the message into multiple smaller intervals between 0 and 1, according to the probability of symbols present in the message.
- Run Length Encoding (RLE) compressed data consists of a series of length and value pairs. Here value is the symbol that is repeated and length is the number of repetitions.

The benefits and drawbacks of the techniques used in the two stages of lossless compression are given in Table 1.

Table 1. Comparison of lossless image compression techniques

Method	Advantages	Disadvantages
Lossless Predictive coding	Simple implementation	Lesser compression ratio
Multi-resolution based coding	Moderate compression ratio	More computational load
Huffman coding	Shortest encoded bit stream with minimum redundancy	Construction and transmission of symbol – probability table
Arithmetic coding	Greater compression ratio and more efficient than Huffman coding	Inaccuracies arise due to the correction mechanism while dividing the intervals
RLE	Faster execution	Lower compression ratio, if there are no repetitions

3.2 Lossy Compression

Lossless compression technique completely removes the redundancy in the image. There is some degradation in the image quality, but there are no visual losses. The rebuilt image will only be an estimate of the input image. Hence, quality measurement is an important metric for this technique. The stages in lossy image compression technique are shown in Figure 2.

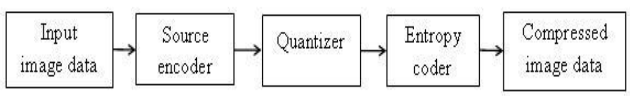

Figure 2. Lossy image compression.

3.2.1 Source Coder

Source encoder is nothing but a linear transformer which reduces the inter-pixel redundancies in the input image. This transform is usually reversible. The commonly used transforms in this stage are:

- Discrete Fourier Transform (DFT) which uses only the sample frequencies that are enough to represent the image in spatial region fully, however the image size is same in both domains.
- Discrete Cosine Transform (DCT) is used to represent image as a sinusoidal sum of components

that vary in magnitude and frequency[11]. Only a few coefficients are needed to represent much of the visually significant information. It has the property of higher energy compaction.

- Discrete Wavelet Transform (DWT) is commonly used for image analysis due to its ability to split the image into finer octave bands in a progressive manner[12]. The advantage of DWT over DFT is that it can provide temporal resolution.

3.2.1.1 Comparison of Source Encoders

DCT and DFT perform similar operations. But DCT is advantageous as more number of sinusoids is needed for accurate representation of the given function using DFT. Table 2 shows the performance comparison of DCT and DWT. As per the experimental analysis of DCT and DWT using TelosB motes[13], DWT is more suited for implementation in WMSN. Though DCT requires lesser memory than DWT power consumption is more[14]. In Table 2 the notation used is * - Low, ** - Moderate, *** - High.

Table 2. Comparison of DCT and DWT

Method	Compression ratio	Processing time	Memory required	Power consumed
DCT	*	***	**	**
DWT	**	**	***	*

3.2.2 Quantizer

Quantization is the process of reducing the bits needed to denote the linearized or transformed coefficients. This step is the reason for lossy nature of the algorithm. Quantization can be applied in various ways like color quantization, frequency quantization, scalar quantization (individual coefficients) or vector quantization (group of coefficients). Generally, quantization is done by means of predefined matrices.

3.2.3 Entropy Coder

In this step the quantized values are further compressed by using any of the lossless compression algorithms like Huffman or Arithmetic or Run length encoder to remove the coding redundancy.

4. Transform based Compression Schemes

The discussion of source encoders for lossy compression concludes the most suitability of DWT for WMSN. Three major compression algorithms using DWT is discussed in this section.

4.1 Embedded Zero Tree Wavelet (EZW) based Compression

EZW[15] belongs to the lossy group of compression techniques. It works on the fact that almost all coefficients out of wavelet transform are nearly zero as the real world images have highly correlated low frequencies. It accomplishes compression using a tree with lower frequency coefficients as the root. Each parent node will have the neighboring higher frequency coefficients as its child. As most of the higher frequency coefficients are zero, there will be more number of sub trees with zero values and hence the name EZW. The importance of the coefficients is evaluated by comparing with a threshold value. Two lists are used in the process one is a dominant list with the indices of the elements that are not designated as significant till now and a subordinate list which has magnitudes of the coefficients that are already marked as significant.

4.2 Embedded Block Coding with Optimized Truncation (EBCOT)

Block based mechanism plays a major role in EBCOT and it is used in JPEG2000 image compression standard[16]. It proceeds by a two stage methodology[17]. In the first phase, the wavelet transformed coefficients are divided into code blocks. Adaptive arithmetic coding is used in the encoding of each block independently. In the second phase the embedded bit stream generated is divided into chunks and packetized by interleaving and packing into diverse layers. The rate control mechanism can be used to truncate the encoded bit stream of each block and to adjust the step size of quantization. It provides facilities for scalability in terms of SNR and resolution.

4.3 Set Partitioning in Hierarchical Trees (SPIHT)

Implementation of SPIHT uses DWT without any entropy coder[18]. Similar to EZW it constructs a tree of transformed coefficients. The significance of coefficients is represented by a binary value. It uses three different lists namely LIP for Insignificant Pixels, LSP for Significant Pixels and LIS for Insignificant Sets. Coding is done in two passes. In the sorting pass significance test for LIP is performed as per the order they are stored in the list and are moved to LSP based on the comparison result. Then significance test is performed on LIS and are moved as set of four elements to LIP or LSP based on the result. Refinement pass is to refine the coefficients in LSP for the bit precision. The process is repeated for all the coefficients by halving the threshold for each pass.

5. Non-Transform based Compression Schemes

Techniques that do not use any transforms have the advantage of reduction in computational load caused by the use of transforms to obtain the frequency domain coefficients. Two algorithms of this kind that can be used in WMSN with some modifications are analyzed in this section.

5.1 Vector Quantization (VQ)

VQ aims at developing a codebook having multiple code vectors each representing image blocks of size m x m[19,20]. The image pixels with higher correlation are grouped into blocks. Then an approximation vector is obtained that can represent every pixel in the block. Encoding is done by comparing the vectors with the codebook and choosing the best matching vector from the codebook. The match is found by calculating the difference of the input and code vector by Euclidean method. Then quantization of this vector is carried out. Once the counterpart is selected, the index of the vector element is used as an alternative for the vector value.

5.2 Fractal Compression

In this method encoding is done based on mathematical theorems. It is well suited for images that have parts that resemble some other parts of the same image. It builds an Iterative Function System (IFS) using Collage and fixed point theorem. The IFS consists of a set of Affain transforms. The image is partitioned into 8 x 8 blocks called as range blocks. A province pool is obtained by the overlapping 16 x 16 blocks. For all range blocks an equivalent is found based on minimum squared error of the Affain transformed domain block[21]. The encoded stream contains quantized Affain transforms, mean of pixel values represented as an offset, location of identical block in domain pool as index and its isometric details.

6. Comparative Analysis

Table 3 summarizes the performance comparison of EZW, EBCOT, SPIHT, VQ and Fractal compression methods based on compression efficiency, processing speed, memory requirement, power consumption, computational load and complexity. EZW and SPIHT are almost equal in terms of performance except the compression ratio and power consumption metrics. Power consumption can be reduced by minimizing the number of passes to find the significant coefficients. EBCOT is found to be the algorithm with higher compression ratio[22]. It is found that about 77% of the processing time is consumed in tier-1 itself[23]. Hence it is not much beneficial for resource constrained WMSN as such. Improvements can be done to reduce the computational load and storage space needed.

Note:* - Low, ** - Moderate, *** - High, **** - Very High

Table 3. Performance comparison of various compression methods

Metric / Method	EZW	EBCOT	SPIHT	VQ	Fractal
Source encoder	DWT	DWT	DWT	Region based clustering	Block partitioning
Coder	Arithmetic coding	Arithmetic coding	Not applicable	Codebook	IFS / interpolation
Compression efficiency	**	***	***	*	****
Processing speed	***	**	***	*	*
Memory required	**	***	**	***	*
Power consumed	***	***	*	***	****
Computational load	*	***	*	****	****
System Complexity	**	***	**	***	***

It can be viewed that SPIHT is more suitable for WMSN as it achieves a very compact encoded bit stream with minimal computational load[24]. It has efficient management of compression ratio, power consumption and complexity over EZW. Only thing to be considered in SPIHT is the memory required to store three different types of lists. This can be overcome by a listless method as proposed in[25]. VQ does not use any transformation and entropy encoding block which reduces the complexity. On the other hand the vector dimension will add to the computational load. To overcome this drawback the codebook design based on wavelet transform and Self-Organizing Feature Maps (SOFM) using Kohonens method is proposed[26]. This makes VQ suitable for WMSN with an increased PSNR value. Fractal compression provides the highest compression ratio of all the five methods[27]. But it is computationally more intensive (finding fractals) and hence increases the power consumption[28].

7. Other Compression Schemes

All the discussed algorithms are Individual Source Coding (ISC) schemes and are implemented in the source node after capturing the image. The complete compression process is carried out in the single node before transmitting to the sink. In hierarchical architecture of WMSN, compression can be performed in multiple nodes. Instead of compressing the image after sensing some portion of compression process can be performed by the camera itself while capturing as in compressive sensing. Compression schemes based on these proposals is discussed in this section.

7.1 Distributed Source Coding (DSC)

In DSC, multiple source nodes send their compressed version of image to the sink. The sink node in turn performs joint decompression based on the many-to-one decoder. This enables the simpler implementation of encoders at the resource constrained source nodes. Complexity is imposed on the decoder implemented in sink node owing to its sophisticated resources. DSC is implemented in sensor fields with overlapping regions[29]. JPEG2000 is also implemented using DSC[30]. In this method the computational load of DWT is distributed between the nodes between the source and target.

7.2 Compressive Sensing (CS)

CS combines the process of compression along with acquisition. This single step process largely leads to the reduction in power consumption. It has the advantage of computational feasibility, stability, no packet loss and robustness against noise. However there is a large gap between the theory and practical implementation of CS. The hardware for CS using a camera that can capture image with single detection element[31] reduces the power consumption.

8. Conclusion

Various characteristics of WMSN; necessity, performance metrics and classification of image compression in WMSN are summarized in the paper. Various methods have been discussed and their drawbacks along with some future research directions for implementation in WMSN are discussed. Among the various ISC schemes SPIHT is found to be more suitable for WMSN. DSC is also well suited and they can reduce the power consumed. In future there are more chances of DSC replacing the ISC schemes. The uniqueness of CS enforces its implementation and the practical challenges will be resolved in the forthcoming years with more advancement in the multimedia hardware technologies. There is no universal method that can serve all the purposes and application needs. Hence the technique to be used solely depends on the requirements of the application and the implementation platform.

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