Efficient Wavelet based Image Compression Technique for Wireless Communication

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Abstract: With phenomenal growth in wireless multimedia image communication, the issues need to handle are resource consumption and the quality of the image being transmitted in wireless channels. The resource consumptions indicated in most literatures are bandwidth and energy consumption. The strict constrains of wireless sensor networks (WSN) on individual sensor node's resource brings great challenges to the information processing, especially in image capture sensor network. A Simple Wavelet Compression (SWC) processing of image coding is proposed to maximize compression and minimize energy cost in WSN. Most of the current work, utilize lossy image compression techniques to minimize the resource consumption. The lossy image compression technique reduces the size of the image to a great extent, however the quality of the image being reproduced needs appreciation. The proposed work presented, an improved polyomines lossless compression technique and efficient wavelet compression, both increases the quality of image at receiving end of the wireless communication by reducing the Peak to Signal Noise ratio and mean square error. Experimental simulation are carried out using JPEG images for evaluating the performance of the improved polyomines lossless compression compared to that of lossy image compression, which shows nearly 20% improvement in quality of image being reproduced on transmitted decompression. The simulation results showed that these approaches achieved significant energy savings without sacrificing the quality of the image reconstruction. Results show up to 80% reduction in the energy consumption achieved by our efficient wavelet compared to a nonenergy-aware one, with the guarantee for the image quality to be lower-bounded.

Keywords: Wireless communication, Image compression, image quality

1. INTRODUCTION

Wireless sensor networks are being developed for a variety of applications such as environmental monitoring, marine biology and video-surveillance.

Several energy efficient protocols of image compression are proposed for wireless applications. The growth of 3G wireless communication systems in line with internet popularity, made wireless multimedia image communication an important research topic in current network communication field. However, representing multimedia data requires a large amount of information, leading to high bandwidth, computation energy (energy consumed in processing information to be transmitted), and communication energy (energy consumed in wirelessly transmitting information) requirements for mobile multimedia communication. The large requirements for bandwidth and energy consumption are significant bottlenecks to wireless multimedia communication.

The characteristic of wireless multimedia communication which can be used to overcome the bandwidth and energy bottlenecks is that the conditions and requirements for mobile communication vary. Variations in wireless channel conditions may be due to user mobility, changing terrain, etc. For example, in [1], the Signal to Interference Ratio (SIR) for cellular phones was found to vary by as much as 100dB for different distances from the base-station. Moreover, the Quality of Service (QoS) – such as transmission latency or bit error rate (BER) – and Quality of Multimedia Data (QoMD) – including image/video quality – required during multimedia communication changes depending on the current multimedia service. For example, the QoS (latency) and QoMD requirements of transmitted data are different between video telephony and web browsing.

One way to design a multimedia capable radio signal which accounts for varying communication conditions and requirements is to assume the worst-case. However, by designing a radio signal, which adapts to current communication conditions and requirements, it is possible to help overcome the bandwidth and energy bottlenecks to wireless multimedia communication. For example, in [2], the authors adapt the channel coding parameters used to match current channel conditions, thereby increasing the average bandwidth available. An algorithm to modify the broadcast power of a power amplifier to meet QoMD requirements, thereby lowering energy consumption is proposed in [3]. In [4], the authors change channel coder and power amplifier settings according to current conditions in order to lower energy consumption. While previous research has studied the effects of adapting the channel coder and power amplifier to current communication conditions and requirements, the effects of modifying the source coder have not been previously studied. The proposed work, presented an improved lossless image compression technique to have an efficient wireless multimedia image compression which utilize the polymonies technique by integrating Huffman code to the noisy transmission channels.

Advances in visual sensors [12], [13] and wireless communication have enabled the development of low-cost, low-power visual multihop wireless networks, which have recently emerged for a variety of applications, including environmental and habitat monitoring, target tracking and surveillance [3], [4]. However, representing visual data requires a large amount of information, leading to high data rates, which in turn requires high computation and communication energy.

2. RELATED WORKS

The proposed work has been inspired by a variety of research efforts in image compression and wireless multimedia communication separately to present an image compression technique which suits the wireless image communication with minimal resource consumption and better quality image at the receiver end. First describe some basic concepts that relates to current research in the area of sensor network applications. The early research efforts in wireless sensor networks did not investigate the issues of node collaboration, focusing more on issues in the design and packaging of small, wireless devices [5], more recent efforts (e.g. [6], [7]) have considered node collaboration issues such as data "aggregation" or "fusion". Our approach of distributed image compression falls within the domain of techniques that apply the concept of in-network processing, i.e. processing in the network by computing over the data as it flows through the nodes. It is worth noting that current aggregation functions (e.g., "maximum" and "average" [7]) are limited to scalar data. Our approach can be viewed as an extension to vector data aggregation.

Previous distributed signal processing/compression problems (e.g. [8], [9]) exploit correlations between data at close-by sensors in order to jointly compress or fuse the correlated information resulting in savings in communication energy. In parallel distributed computing theory [10], a problem (or task) is divided into multiple sub-problems (or sub-tasks) of smaller size (in terms of resource requirements). Every node solves each sub problem by running the same local algorithm, and the solution to the original problem is obtained by combining the outputs from the different nodes. Our approach to the design of distributed image compression is similar in concept, in that we distribute the task of image encoding/compression to multiple smaller image encoding/compression sub-tasks. However, a key difference is that distributed computation theory typically focuses on maximizing the speed of execution of the task while our primarily concern here is reducing the total energy consumption subject to a required image quality. Thus, our proposed approach of image compression intersects with the literature on lossy and lossless compression, which primarily focuses on polyomino technique.

R. S. Wagner [14] uses the down sampling from each camera node that have the common image. Thus low resolution image is sent from each node that causes the energy consumption. Min Wu et al. [15] sent only the changes from each node that has the common image. This also have overhead of communication from each node and also considered that background is stationary.

3. LOSSLESS IMAGE COMPRESSION USING IMPROVED

POLYOMINO

There are two types of image compression: lossless and lossy. After decompression the original image is recovered. The steps shown in the diagram are invertable, hence they are lossless except for the quantize step to take place. Quantizing refers to a reduction of the precision of the floating point values of the wavelet transform, which are typically either 32-bit or 64-bit floating point numbers. To use less bits in the compressed transform which is necessary if compression of 10 bpp or 14 bpp images is to be achieved these transform values must be expressed with less bits for each value. This leads to rounding error. These approximate, quantized, wavelet transforms will produce approximations to the images then an inverse transform is performed. Thus creating the error inherent in lossy compression.

Compressing an image is significantly different than compressing raw binary data. The general purpose compression is used to compress images, but the result is less than optimal. This is because images have certain statistical properties which can be exploited by encoders specifically designed for them. This also means that lossy compression techniques can be used in this area.

An integer-to-integer wavelet transform produces an integer-valued transform from the grey-scale, integer-valued image [11]. Since n loops in Bit-plane encoding reduces the quantization error to less than $T0/2^n$, it follows that once 2^n is greater than T0, there will be zero error. In other words, the bit-plane encoded transform will be exactly the same as the original wavelet transform, hence lossless encoding is achieved . Lossless compression involves with compressing data which, when decompressed, will be an exact replica of the original data.This is the case when binary data such as executables, documents etc. are compressed. They need to be exactly reproduced when decompressed. On the other hand, images (and music too) need not be Reproduced 'exactly'.

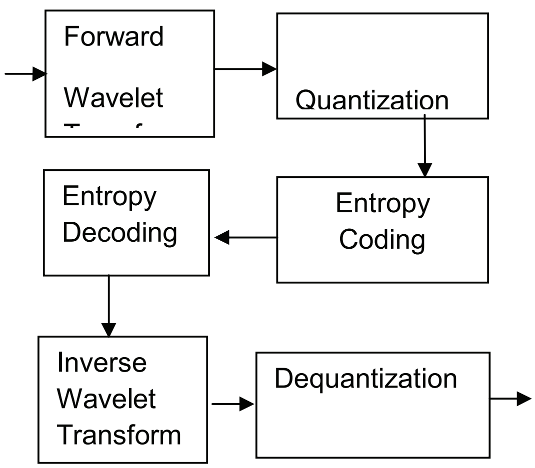

Fig 1 A typical Wavelet Based Image Compression (a) Encoder (b) Decoder.

A typical wavelet based image compression system is shown in Fig. 1. It consists of three closely connected components namely Forward/ Reverse transformer, Quantizer / Dequantizer and Entropy encoder/decoder. In terms of energy dissipation of JPEG2000 compression/decompression, wavelet transform is the dominant part.

3.1 Error Metrics In Wavelet based image compression.

Two of the error metrics used to compare the various image compression techniques are the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$MSE = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} \left[I(x,y) - I'(x,y) \right]^2 \quad + \ MN$$

MSE = 1 / MN Σ Σ [I (x,y) – I' (x,y)] ^{2} + MN

y = 1 to M ; x = 1 to N

PSNR = 20 * log10 (255 / sqrt(MSE))

where I(x,y) is the original image, I'(x,y) is the decompressed image and M,N represents dimensions of the images. A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. The signal is the original image, and the noise is the error in reconstruction. It is highly required to evaluate a compression scheme having a lower MSE (and a high PSNR).

3.2 Compression Algorithm

There are numerous ways to compare between two compression algorithms. The metrics are different for lossless and lossy compression schemes. For lossless compression scheme, the first parameter to be compared is the compression ratios. Second, we check the time complexity and the memory requirements. Any lossless compression scheme, which yields higher compression ratio, lesser time complexity and requires lesser memory, is accepted to be a better lossless compression algorithm.The quality of the decompressed image is measured in terms of PSNR (Peak Signal to Noise Ratio) value. The decompressed image having the higher PSNR value is assumed to have retained better image quality of the original image. It is inversely proportional to the mean square error (MSE). The more the error, the less will be the PSNR value and vice versa. PSNR value is infinite for lossless image compression because the MSE value is zero in lossless compression. Hence, any lossy compression scheme, which gives more PSNR value and more compression ratio, is accepted to be the better compression algorithm.

3.3 Wavelet Image Compression

Lossy JPEG compression introduces blocky artifacts in the decompressed image, which are not desirable and pleasing to the eyes. Lapped Orthogonal Transforms (LOT) [7] was proposed to solve this problem by using smoothing the overlapping blocks. LOT could reduce the blocking effects but its computational complexity is very high and hence LOT is not preferred to use over JPEG. On the other hand, wavelet based image compression introduces no blocky artifacts in the decompressed image. The decompressed image is much smoother and pleasant to eyes. We can also achieve much higher compression ratios regardless of the amount of compression achieved. By adding more and more detail information we can improve the quality. This feature is attractive for what is known as progressive transmission of images.

Another lossy compression scheme developed for image compression is the fractal base image compression scheme [1]. However the fractal based image compression beginning to loss ground because it is very complex and time consuming.Wavelet signifies small wave. It was first used in approximating a function by linear combination of various waveforms obtained by translating and scaling the wavelet at various position and scales. It was very old from the time of Alfred Haars. But it was not so popular then because it found no application area. It becomes popular only when Ingrid Daubechies [5] shows that QMF (Quadrature Mirror Filter) filters [6] used in filterbank for subband coding can be generated from the wavelet by using the perfect reconstruction relation of the filter bank. So, what we obtain from the wavelet is a set of QMF filter banks that can be used for subband coding. In a QMF filter bank a signal is first decomposed into low pass and high pass components using low filters. The filter components are reduced their size by half either by rejecting the even or odd samples thereby the total size of the original signal is preserved. The low pass filter component retains almost all distinguishable features of the original signal. And the high pass filter component has little or no resemblance of the original signal. The low pass component is again decomposed into two components.

The decomposition process can be continued up to the last possible level or up to a certain desired level. As the high pass filter components have less information discernible to the original signal, we can eliminate the information contents of the high pass filters partially or significantly at each level of decomposition during the reconstruction process. It is this possibility of elimination of the information contents of the high pass filter components that gives higher compression ratio in the case of wavelet based image compression.

4. EXPERIMENTAL EVALUATION ON LOSSLESS IMAGE COMPRESSION TECHNIQUES

The experimental evaluation is carried out with the original image given as the input. The image is compressed at the rate of 50 %. Image compression is done for lossless compression, lossy compression and wavelet compression. The quality rate applied for all the compression technique is 50% carried out with the JPEG image golf.jpg. In the filtering phase the wavelet based image compression does not reduce the dimension of the image , height or width to compress but it transforms it values in order to obtain a more compressible set of data. The filtering phase comprises of standard filtering, color filtering and remapping.Just to show how wavelet based image compression is performed, a simple image compression example is given here. Fig-1, is the original image. It is decomposed up to two levels using 9/7 biorthogonal filters.

Original Image

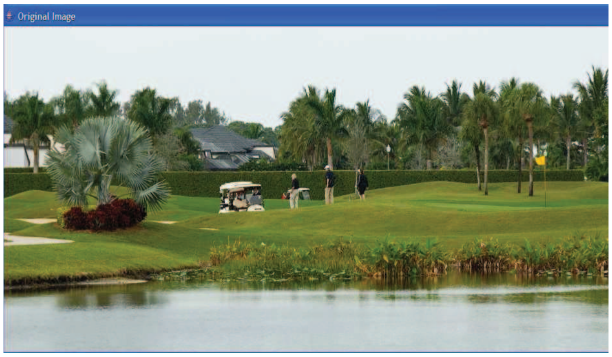

Fig 1. Original Image

Lossless Compression: At quality rate 50%

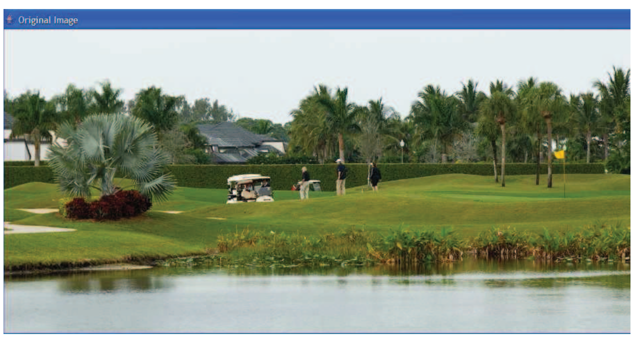

Fig 2. Lossless Compression applied to the original image

Lossy Compression:At quality rate 50%

Fig 3. Lossy Compression applied to the original image

Wavelet Compression : At quality rate 50%

Fig 4. Wavelet Compression applied to the original image.

There are one low pass components and six high pass components. The low pass component is also most often referred to as approximation component as it basically represents the approximation of the original signal or image. The high pass components are often referred to as details. So, in figure- 2, the top leftmost corner, the rest are the details. We see that the approximation component represents fairly the original signal even it has been reduced four times in size. Figure-3 gives the decompressed image from the 16 times compressed data. And figure 4-d shows the decompressed image from the 32 times compressed data. However, we see that these decompressed image are visually similar to the original image. However, they are very different numerically. This is how the lossy compression works. Using wavelet based image compression we can compress an image up to 128 times, still we would get distinguishable approximation of the image. From the table above it is clear that the wavelet image based compression proves to be highly preferable when compared to the lossless compression and lossy compression.

5. RESULT AND DISCUSSION

There are a wide variety of wavelet-based image compression algorithms besides the one that we focused on here. Some of the most promising are algorithms that minimize the amount of energy which the encoder and/or decoder must use. A new algorithm which is embedded and which minimizes energy is described . Many other algorithms are cited in the review article [1]. In evaluating the performance of any new image compression algorithm, one must take into account not only wavelet values, but also consider the following factors: (1) perceptual quality of the images (edge correlation values can be helpful here), (2) whether the algorithm allows for progressive transmission, (3) the complexity of the algorithm (including memory usage), and (4) whether the algorithm has ROI capability.

In this section, we perform two sets of simulations that compare our proposed wavelet compression with the centralized algorithm based on two performance metrics : energy consumption and system lifetime. Our simulations are compared with the lossless compression and lossy compression. Results show that though the size of the bytes has been reduced considerably the result after the compression algorithm has not been changed. The image is same as to the original image. From the table we can conclude that as the value of the quality increases in lossless compression we obtain 117331 bytes, in lossy compression we attained 97744 bytes and in wavelet compression we gained 105422 bytes. Compared to the three compression techniques, wavelet compression results with the reduction of bytes without changing the original image. As though we compress the image and then transmit considerable amount of energy is utilized. This energy consumption is also reduced to the maximum possible and then the image after being compressed is transmitted.

TABLE 1: LOSSLESS COMPRESSION

Source Image: Golf.jpg

[596 kb or 610414 bytes]

Quality	20	40	60	80
Size (bytes)	38224	58631	77064	117331

TABLE 2 : LOSSY COMPRESSION

Source Image: Golf.jpg

[596 kb or 610414 bytes]

Quality	20	40	60	80
Size (bytes)	31976	48838	64501	97744

TABLE 3: WAVELET COMPRESSION

Source Image: Golf.jpg

[596 kb or 610414 bytes]

Quality	20	40	60	80
Size (bytes)	37249	56753	75173	105422

6. CONCLUSION

The proposed work presented an improved wavelet based inductive methods for lossless image compression ,lossy image compression and the wavelet image compression which can be effectively deployed in the transmission of wireless communication. The experimental simulation conducted for the standard JPEG images, by applying the three compression techniques in the wireless channel, shows better quality of image on decompression (nearly 25%) compared to that of any other technique. By adapting the source code of a multimedia capable radio to current communication conditions and constraints, it is possible to overcome the bandwidth and energy bottlenecks to wireless multimedia communication.

In the proposed scheme we have selected two parameters of the efficient wavelet image compression algorithm to vary, and presented the results of modifying the parameters on quality of image, computation and communication efficiency with respect to energy utilization. We are planning to extend the proposed work to improve on the line of evaluating the performance of the image compression technique to latency and data loss occurrence during the image transmission on the wireless communication channel. The impact of this scheme on image signal quality is presented in the final. The simulation results showed that these approaches achieved significant energy savings without sacrificing the quality of the image reconstruction.

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