

**A STUDY OF MULTIPLE IMAGE COMPRESSIONS USING WAVELETS
IN MEDICAL IMAGING**

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ABSTRACT

The preceding chapter's primary goal was to examine a typical wavelet transform application to ECG medical pictures, which are crucial for identifying cardiac disorders. In this study, we investigate how multiple image compression, a cutting-edge method, may be used to apply wavelet transform to MRI. Since ancient times, information has been transmitted via images and pictures. These were formerly shown physically, such as via stone etching or carving on cave walls. This approach develops gradually and steadily, and now images and films are represented electronically; yet, their transmission and storage are entirely unrelated to their presentation. Digital image storage expands the options for picture representation. To save a picture digitally and transform it back for suitable display, there are several algorithms available. Image coding is the process of altering an image's representation such that its storage and representation may be acquired with the least amount of data. Picture compression is used when storing a representation of an image that uses less space than the original.

KEYWORDS: Multiple Image, Compressions, Wavelets, Medical Imaging, ECG medical pictures, wavelet transform, Digital image storage.

INTRODUCTION

In order to compress an image more accurately and efficiently, this chapter explores a range of approaches that employ several resolutions and various wavelets. One kind of encoding is progressive encoding, which is sometimes called embedded encoding. As more bits are added, progressive encoding becomes more accurate. The process is similar to finding the value of a number with more digits added after the decimal point, which increases its accuracy. Adding additional bits to the bit stream will result in a decoded image with more information to display.

Furthermore, due to storage space constraints and predetermined accuracy standards, bit streams might be constrained to a restricted number of bits.

NEEDFORCOMPRESSION

An essential part of data is shown by a picture in almost every discipline; examples include aerospace engineering, biomedical engineering, geographic science, statistics, and astronomy. A great deal of information is sent and stored in a computer system as images and results when we speak about biomedical engineering.

The limitations of today's computer systems, however, do restrict us in certain ways. Consequently, image compression is the best choice for optimizing storage and bandwidth. Compressing images virtually gets rid of coding, interpixel, and psycho-visual redundancy. Inefficient code representing an image leads to coding duplication. The individual pixels that compose an image are highly related to one another. The emergence of interpixel redundancy is caused by these pixel correlations. Psychovisual redundancy occurs when the human visual system fails to register seemingly insignificant portions of data (Sonal, 2005). Common types of data redundancy include spatial, temporal, and spectral. The need to repeat information increases due to spatial redundancy, which occurs when neighboring pixels in an image are linked to one another. The concept of temporal redundancy arises from the idea of compressing video from the perspective of identically placed pixels in different frames of a movie. Associating several color planes causes the spectrum to become redundant. The reconstructed image's quality drops because the color plane loses some of its distinctiveness during compression and decompression.

BENEFITSOFIMAGECOMPRESSION

With the advent of the World Wide Web, image compression has the potential to both reduce the storage requirements of web hosts and increase the loading and uploading speeds of photographs. Reducing file sizes is a crucial part of storing numerous images in a compact area and reducing overall execution time. It is more likely that error-free photos will be transferred at lower bandwidth as the number of bits sent decreases. So, even on older, slower devices, pictures load much faster. Any worries about the expense of sending images, say, via a phone network, are

fully addressed. Unauthorized monitoring does increase safety measures to some degree.

TECHNIQUES OF IMAGE COMPRESSION

There are currently a number of picture compression algorithms, and many articles on the subject have appeared in scholarly journals both at home and abroad. If an algorithm can generate a lossless or lossy reconstructed image, then it is likely to be chosen. Because of this, it seems like we can broadly categorize all compression algorithms as lossy or lossless. Just looking at the name gives it away: the lossless method produces decompressed pictures with the same bit stream as the original. When a single bit is missed, this type of approach is useful.

Nullify the contents of a file, including any code it may contain. Lossy approaches, on the other hand, modify the bit stream after decompression. When using the lossy method, some data is disregarded, leaving just the visually appealing portions. What we have here is VLC, or visually lossless compression. Using these methods might help reduce the file size of biological images, films, or audio (Soloman, 2005). The compression ratio provided by this approach is much higher than that of the lossless method.

Lossless compression makes use of a variety of encoding techniques, including deflate, run length encoding, chain codes, and entropy encoding. Modern VLC methods include wavelet transform, fractal compression, and discrete cosine transform in that order of popularity. Strategies that center on the wavelet transform will get the bulk of our attention.

MEASURES TO ASSESS QUALITY OF COMPRESSION

Nowadays, there are a plethora of performance criteria that are used to assess the caliber of image compression. Several examples of statistical measures include peak signal-to-noise ratio (PSNR), average difference, normalized cross correlation, structural content, Laplacian mean square error, and picture quality scale area. Here are a few of the most common:

Compression ratio (CR): It is the proportion of the size of original image (m) to the size of compressed image (n). Its explicit notation is $m : n$.

Peak Signal to Noise Ratio (PSNR): The ratio of a signal's supreme potential to the power of a noisy signal, which impacts the signal's dependability, is defined by this manufacturing phrase. On the logarithmic decibel scale, it is represented in dB. Having the image described in bits per pixel is beneficial. If each picture pixel is represented by an 8-bit sample, then the number of samples is 8. Below is the definition of PSNR:

$$\begin{aligned} PSNR &= 10 \log_{10} \left(\frac{(2^n - 1)^2}{MSE} \right) \\ &= 10 \log_{10} \left(\frac{255^2}{MSE} \right) \end{aligned}$$

Here, MSE symbolizes Mean Square Error and n signifies bits per sample. **Mean**

Square Error (MSE): To calculate it, take the square of the difference between the original and reconstructed images and divide it by the total number of picture components. In mathematical terms, it is given as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} |X(i, j) - X_c(i, j)|^2$$

It always gives non-negative value. If the value of MSE is closer to zero then it is considered as better.

Maximum Error: It provides, as its name suggests, the greatest divergence between the original and reconstructed images, which is used in image compression..

Bits per pixel ratio (BPP): The number of bits required for storing or transmitting data is shown as bits per pixel. Multiplying the compression ratio by 8 yields the bits per pixel ratio, in the case when each pixel contains 8 bits, or one byte. When considering pixel storage, it is common practice to use 8 bits per pixel; however, the standard bit per picture (BPP) for full color photos is 24. As the bit rate increases, the picture quality becomes better.

COMPRESSION USING WAVELET PACKETS AND BIORTHOGONAL WAVELETS

We all know that wavelet-based approaches have performed well when it comes to compressing pictures. Wavelet packet and biorthogonal wavelet based algorithms outperform state-of-the-art wavelet filter approaches in a large number of experiments. Wavelet packets from several wavelet families may be considered for multiple compressions, along with 2D products and multi-wavelets. There are more filters used in wavelet packet decomposition than in DWT. The trade-off is increased computational complexity due to more sophisticated features and bit stream scalability.

Depending on the situation, worldwide technology constraints could impact the decisions about wavelets and wavelet packets. The quality of the reconstructed image is somewhat affected by each compression option. Algorithms based on biological wavelets are known to provide lossy or almost lossless compression. One famous technique that uses the discrete wavelet transform and the biorthogonal basis of Daubechie's wavelet is JPEG2000. Computers with advanced processing capabilities handle large image blocks with little contrast. Software that operates on the JPEG2000 standard. Medical pictures, such as those from computed tomography (CT) and magnetic resonance imaging (MRI), are big imagefiles, and these tools are helpful for running them.

STEPS INVOLVED IN IMAGE COMPRESSION

Transformation:

Pixels are often believed to be the building blocks of images. A lot of data is redundant since these pixels are highly correlated with one another. Before the thresholding operation decorrelates the pixel, the coding strategy converts the original image's pixels into frequency domain coefficients. Some of the methods used for this purpose include discrete cosine transform (DCT), discrete fourier transform (DFT), slant-haar transform (SHT), hadamard-haar transform (HHT), short fourier transform (SFT), karhune-loeve transform (KLT), and discrete wavelet transform. These modified coefficients exhibit the required properties, including energy compactness, upon application of any of the aforementioned methods. Because most of the energy is concentrated in a few altered coefficients, energy compression is a significant phenomenon (Mark and Michel, 1992). We conducted

comparative studies using several members of the wavelet family and zeroed in on the wavelet-based DWT technique.

Quantization and Thresholding:

Following the application of DWT, a threshold value should be set to exclude insignificant wavelet modified coefficients. Ignored coefficients are of limited utility since they do not provide much information. During the separation phase, the technique is used to iteratively adjust a threshold value. Elements are removed when their coefficient values drop below a certain threshold. This is an important removal step since it affects the compressed image quality. The remaining coefficients are quantized using the quantization factor. Essentially, it makes entropy encoders more understandable by converting floating-point coefficients to integers. There is a decrease in image quality due to threshold and quantization. When dealing with higher numbers, a considerable amount is disregarded when comparable processes are repeated. When executing many compressions, you must be very careful when selecting these values.

Entropy Encoding:

This completes the compression strategy. Entropy primarily identifies symbols in compressed bit streams that often coexist with the same code words. Bits created as a consequence of the quantization process are reduced as a result. The three coding methods employed are differential pulse coding, run length encoding, and Huffman coding. According to the definition of general function flow, each quantized value is given certain probabilities using a predetermined technique. Code words are allocated based on the probability associated with specific symbols. Then, to prevent repetition, these code phrases are carefully examined. In this manner, the number of bits is decreased to the minimum amount necessary to represent the picture. The decoder precisely reverses the encoding process for decompression and rebuilding. Arithmetic encoders and Huffman encoders are the two kinds of coders employed in this operation. Due to the fractional amount of bits required for encoding, the arithmetic encoder is mostly utilized in wavelet-based approaches. The Huffman encoder employs integer numbers for each code rather than allowing fractional numbers orbits.

Let us consider image decomposition coefficient $\{V_i\}$ of an image. Let nonnegative quantity defined as entropy be $\epsilon^2(\{V_i\})$. This

entropy is associated with each set of $\{V_i\}$ defined as follows:

$$\epsilon^2(\{v_i\}) = - \sum_i \frac{v_i^2}{\|v\|^2} \log_2 \frac{v_i^2}{\|v\|^2} \quad \text{Here, } \|v\|^2 = \sum_i v_i^2.$$

The number of components that characterize the picture in a certain basis is given by this definition of entropy. It is believed that the best foundation is the one that produces the least amount of entropy.

ALGORITHMS FOR IMAGE COMPRESSION USING WAVELETS

Well known procedures for image compression with wavelet as main component is described below:

Embedded Zerotree Wavelet (EZW):

The very simple EZW algorithm was suggested by Shapiro (1993). When an encoder creates two files, the first few bits of the larger file will include the smaller file, which corresponds to the smallest file size. This is what the term "embedded" means in the context of EZW. This method is based on the lossy technique and employs bit plane encoding during the embedding step. Transformed coefficients are shown by trees. Root nodes are formed by the lowest frequency coefficients, while the subsequent higher frequency sub-bands are filled by the progeny of a root node. Subtrees called zero trees are constructed using wavelet transformations that produce coefficients with values of zero or almost zero at high compression ratios. A coefficient is considered important if and only if its magnitude is greater than some predetermined threshold. At the beginning, it is kept closer to this threshold value, and the maximum coefficient value decreases by a factor of 2 with each iteration. By comparing the threshold value to a range of significant coefficients, we may derive the normal compressed form of a picture. In order to provide additional information, this array adds more and more significant coefficients.

CONCLUSION

In this chapter, we compared the efficiency and reliability of multiple compression on a gray scale MRI picture from the medical industry with a real color image of

fruit for demonstration purposes. We calculated and compared measurement metrics including PSNR, CR, MSE, and BPP, and we used several methods based on wavelet and wavelet packet compression techniques. When it comes to storing and retrieving/transmitting pictures, this comparative and exploratory research found that using double or triple compression frequencies favorably improved performance. But further compression could cause data loss and poor picture quality. But if implemented in the medical industry, this approach has the potential to radically alter the way we save and share patient records, both in the event of an emergency and in the future. The ideal wavelet basis and level for different compression frequencies may be estimated with the help of these experiments. Coding in lossy mode at low bit rates causes the backdrop to become fuzzy; this may be overlooked if the visual element includes vital information. The topic of picture and video compression has been the subject of several publications and articles. New approaches are invented every decade, each one an advance over the last. A novel wavelet-based approach called Geometric wavelet (GW) has just been created. Results for GW performance metrics in terms of PSNR and CR are improved. The same holds true for the presentation of new algorithms; they might be based on comparison studies and experimental findings that have been enhanced or modified from previous approaches. The current high-tech age brings new compute approaches that boost efficiency while decreasing execution time and code operation complexity.

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