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AN IMPROVED TECHNIQUE TO WAVELET THRESHOLDING AT DETAILS SUBBANDS FOR IMAGE COMPRESSION

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ABSTRACT

This paper will address a new proposed algorithm using wavelet properties to compress an image. It is based on the concept of reducing the near-zero wavelet coefficients at detail subbands (Diagonal, Vertical and Horizontal). This approach is inspired by formerly known Hard Thresholding that eliminate all the coefficient under the fixed threshold value while keeping up the rest. Here, we proposed our own threshold value estimation based on standard deviation concept to find the optimal threshold value at each details subbands. Throughout the experiment done, we found that the proposed algorithm can effectively remove a large amount of unnecessary wavelet coefficient without harming the image quality while increasing the compression ratio and reducing the elapse time.

Keywords: discrete wavelet transforms, wavelet coefficients, threshold.

INTRODUCTION

Uncompressed multimedia (graphics, audio and video) data requires considerable storage capacity and transmission bandwidth. Despite rapid progress in mass-storage density, processor speeds, and digital communication system performance, demand for data storage capacity and data transmission bandwidth continues to outstrip the capabilities of available technologies (Md Taujuddin and Ibrahim, 2014).

As for example, the typical digital chest X-ray, 2000 x 2500 pixels, with 10-12 bits per pixel takes up to 10 Megabytes in the archive. Despite the technological advances in storage and transmission, the demands placed on the storage capacities and on the bandwidth of communication exceed the availability (Wong, Zaremba, Gooden, and Huang, 1995) (Kofidis, Kolokotronis, Vassilarakou, Theodoridis, and Cavouras, 1999) (Burak, Carlo, Bernd, and Chris, 2001) (Janaki, 2012).

Therefore it is crucial to compress the image by storing only the essential information needed to reconstruct the image.

IMAGE COMPRESSION

An image can be thought of as a matrix of pixel (or intensity) values. In order to compress the image, redundancies must be exploited, for example, areas where there is little or no change between pixel values. Therefore large redundancies occur in the images which having large areas of uniform colour, and conversely images that have frequent and large changes in colour will be less redundant and harder to compress.

There are two ways of classifying compression techniques (Subramanya, 2001):

A. Lossless vs. lossy compression: In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression. An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression. Under normal viewing conditions, no visible loss is perceived (visually lossless).

B. Predictive vs. transform coding: In predictive coding, information already sent or available is used to predict future values, and the difference is coded. Since this is done in the image or spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients). This method provides greater data compression compared to predictive methods, although at the expense of greater computation.

Before examine the algorithm for more details, we shall outline the basic steps that are common to all wavelet algorithm image compression. The stages of compression and decompression are shown in Figure-1 and Figure-2.

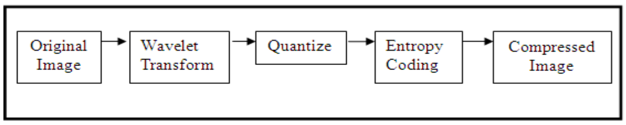

Figure-1. Compression of an image (K. Sahi, 2002).

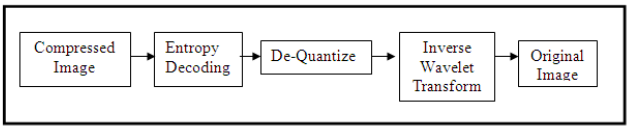

Figure-2. Decompression of an image (K. Sahi, 2002).

All of the steps shown in the compression diagram are invertible, hence lossless, except for the Quantize step. Quantizing refers to a reduction of the precision of the point values of the wavelet transform, which typically either 32 or 64 bit point numbers. To use less bits in the compressed transform which necessary if compression of image to be achieve, these transform value must be expressed with less bits of each value. This leads to rounding error. The wavelet transform will approximation to the images when inverse transform is performed.

In order to compress the image, Wavelet analysis can be used to divide the information of an image into approximation and detail sub-signals. The approximation sub-signal shows the general trend of pixel values, and three detail sub-signals show the horizontal, vertical and diagonal details or changes in the image. If these details are very small then they can be set to zero without significantly changing the image.

The value below which details are considered small enough to be set to zero is known as the threshold. The greater the number of zeros the greater the compression that can be achieved. The amount of information retained by an image after compression and decompression is known as the energy retained and this is proportional to the sum of the squares of the pixel values.

If the energy retained is 100% then the compression is known as lossless as the image can be reconstructed exactly. This occurs when the threshold value is set to zero, meaning that the detail has not been changed. If any values are changed then energy will be lost and this is known as lossy compression.

Ideally, during compression the number of zeros and the energy retention will be as high as possible. However, as more zeros are obtained more energy is lost, so a balance between the two needs to be found.

Many Wavelets generic being introduced nowadays that produce smoother and more satisfactory compressed image. Some of the prominent compression algorithm that offer the lowest error per compression rate with highest perceptual quality image conveyed are EZW, SPHIT, WDR and ASWDR.

i. Embedded zerotree wavelet (EZW)

EZW uses the concept of ‘parent-child’ dependencies between subband coefficients at same spatial location. It produces encoded bits in specific order of importance (Shapiro, 1993).

The EZW can approximate the image in bitplane-by-bitplane style while prioritizing the wavelet coefficients according to their magnitude. It also exploit the correspondence of spatially related pixels within different subband but in the same bit plane by using zero-tree concept. It will produce significant map or binary map that represent the significance of wavelet coefficients compared to a successively decreasing threshold values.

EZW perform well on the image with frequent occurred wavelet coefficient value. This is because it can produce many zerotrees especially when high threshold is applied. EZW is using Discrete Wavelet Transform (DWT) to transform the image and embedded coding is done by using Successive Approximate Quantization (SAQ) (Loganathan & Kumaraswamy, 2013) (Shapiro, 1993).

ii. Set partitioning in hierarchical trees (SPHIT)

The different amongst SPHIT and EZW is the way trees of coefficients are portioned and sorted (Said, Pearlman, and Member, 1996). While the uniqueness of SPHIT is its compactness. The bitstream from SPHIT algorithm is so compact that passing it through an entropy coder would only produce very insignificant gain in compression. No ordering information is explicitly transmitted to the decoder. As an alternative, the decoder reproduce the execution path of the encoder and recovers the ordering information

iii. Wavelet different reduction (WDR)

The improvement made on WDR is the way on how it encode the position of the significant wavelet transform value. This is an alternative approach from the previous SPHIT indirectly locates the position of significant coefficients.

As example, the significant values are $w(3) = -33.5$, $w(7) = +48.2$ and $w(12) = +40.34$. Their indices are 3,7 and 12. So, their successive differences are 3,4 and 5 with the first index is the starting number followed by the difference value. The binary representation is $(11)_2$, $(100)_2$ and $(101)_2$. Since all the first bit is 1, so it can be dropped and the significant sign is used as separator. The resulting output is -1+00+01. So here it get the name of Wavelet Difference Reduction.

WDR produce low bit rate reconstruct image in effect of the decoding process can be terminated at any point.

iv. Adaptive scanned wavelet different reduction (ASWDR)

The enhancement of ASWDR it only improve the scanning order of WDR in predicting the new significant value to get higher performance (Walker, 2000). This process produces a smaller length of symbol string for encoding the distances.

Besides, the ASWDR produce more significant value because it use a better predictive scheme. One of the advantage of ASWDR is can protect the details at low bit rates and it was beneficial for medical imaging.

PROPOSED TECHNIQUE

The EZW, SPHIT, WDR and ASWDR initializing its threshold value T, by randomly choose the wavelet coefficient value, w(m) that satisfy $|w(m)|<T$, and at least one value satisfy $|w(m)| \geqslant T$. This value is then reduced by half (T/2) for each consequent loop. This approach is very simple and low computational cost, but it just can produce a good threshold value for high correlation natural image.

To overcome this problem, some previous researchers have provided their own solution. (Benzid,

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Marir, Boussaad, and Benyoucef, 2003) suggests a technique of fixing the percentage of wavelet coefficient to zeroed. This technique is actually implemented and works well for ECG data signal.

Other researcher, (Baligar, 2006) is suggesting a method of fixing threshold value before performing the compression task. Using this approach, the edge is compressed without lost while the rest is compressed using near loss or lossless compression method.

While, Arya in her paper (Devi and Mini, 2012) proposing a technique which predicting the wavelet coefficient based on the past neigbouring sample. Yet, this technique just works well for images which made of smooth region separate by smooth boundary.

On the other hand, these approaches accommodate all subband as equal, leaving the different features of wavelet coefficient unexploited. Hence, here we provide an alternative approach that consider the diversity character of wavelet coefficient subsequently in each separated detail subband. Detail subbands consist of Diagonal, Vertical and Horizontal subband.

So, in this project we are proposing new threshold estimation based on the standard deviation concept. After applying the Discrete Wavelet Transform (DWT) to an image, wavelet coefficients are generated. It consist of one approximate subband and three details subbands. The details subband comprise of horizontal, vertical and diagonal subband that carries the respective detail information.

In our algorithm, we leave the approximate subband unchanged because modification at this subband will destroy a large amount of significant coefficients that may lead to lossy compression (Sánchez *et al.*, 2004).

While the detail subband contain a very large amount of ‘near-zero’ wavelet coefficient that doesn’t effect the image quality even this value is discarded. This is because the ‘near-zero’ wavelet coefficients is actually represent the smooth region where modification at this area are actually not easily been detected by Human Visual System (HSV) (Taujuddin, Ibrahim, and Sari, 2015).

Discarding the ‘near-zero’ coefficient at detail subband is actually will reduce a high amount of wavelet coefficient. Thus, it will lead to a higher compression ratio without degrading the image quality.

The wavelet coefficients representation can be expressed as follows:

a. Diagonal subbands, $\omega_{\varphi}^{D}(j_0, k_1, k_2)$,
b. Vertical subbands, $\omega_{\varphi}^{V}(j_0, k_1, k_2)$
c. Horizontal subbands, $\omega_{\varphi}^{H}(j_0, k_1, k_2)$

By applying the standard deviation concept to each respective detail subband, we derive our new threshold estimation equation.

$$\lambda_y = \left(\frac{1}{n}\sum_{i=1}^{n}(\omega_{\varphi}^{y}(j_0, k_1, k_2) - \bar{x})^2\right)^{1/2} \quad (1)$$

Where;

y is representing either diagonal subband (D), vertical subband (V) or horizontal subband (H);
n is the amount of wavelet coefficients in respective subband;

ω_{φ} is wavelet filter;
j_0 is the wavelet scale;
k_1 and k_2 are the index written from image function;
$\bar{x}$ is the mean value of wavelet coefficient at respective subband.

Each wavelet coefficients that is higher than our derived threshold value, λ_y, is retained while the rest, which is considered as the ‘near-zero’ coefficients are discarded. So, the new remaining detail coefficients can be expressed as:

$$\omega_{\varphi}^{y}(j_0, k_1, k_2)_{new} = \begin{cases} \omega_{\varphi}^{y}(j_0, k_1, k_2), & |\omega_{\varphi}^{y}(j_0, k_1, k_2)| \geq \lambda_y \\ 0 & , |\omega_{\varphi}^{y}(j_0, k_1, k_2)| < \lambda_y \end{cases} \quad (2)$$

This concept is actually inspired from the previous well-known hard thresholding concept (Donoho and Johnstone, 1993).

RESULT AND ANALYSIS

This experiment is carried out on Matlab by using three standard test images, namely House, Mandrill and Boat. To evaluate the performance of the proposed algorithm, we compared it with the prominent wavelet-based compression algorithms such as EZW, SPIHT,WDR and ASWDR on Peak Signal to Noise Ratio (PSNR), compression ratio and elapse time. A more detail discussion on this performance test can be found at (Kourav and Sharma, 2014).

As can be observed from Table-1, the quality of the final reconstructed image by using our proposed compression algorithm is superior compared to the prominent one. The previous algorithm doesn’t concern in preserving the edges and fine details of an image. So, obviously it resulting in an over smoothing effect at the edges and fine details such as at the brick of the wall, the wrinkle of the mandrill face and the body of the boat.

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Table-1. Final reconstructed image by using various wavelet-based compression algorithm and the proposed algorithm.

Algorithms\ Images	House	Mandrill	Boat
Original			
EZW			
SPIHT			
WDR			
ASWDR			
Proposed			

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Table-2. Performance test on previous wavelet-based compression algorithm with the proposed algorithm.

Image: House			
Algorithms	**PSNR**	**Compression ratio**	**Elapse time**
EZW	28.6607	2.6718	1.2962
SPIHT	27.9179	1.7914	1.0149
WDR	28.6801	2.6794	0.9173
ASWDR	28.6801	2.6306	1.4415
Proposed	44.7872	5.7672	1.3492
Image: Mandrill			
EZW	25.3458	3.7109	3.6233
SPIHT	24.8944	2.6409	2.5622
WDR	25.3458	3.9112	2.5622
ASWDR	25.3458	3.9032	3.8441
Proposed	40.0860	6.2493	1.7052
Image: Boat			
EZW	27.0949	2.4998	8.8754
SPIHT	26.6083	1.7052	6.5309
WDR	27.0949	2.6451	4.9074
ASWDR	27.0949	2.6245	8.0349
Proposed	43.9563	4.6037	1.7882

Our proposed algorithm also clearly outperforms the other four aforementioned algorithms in terms of PSNR, compression ratio and elapse time. The proposed algorithm effectively restore the significant coefficients and it clearly shows in PSNR value. As can be seen in both Table-1 and Table-2, PSNR value of the proposed method is over than 40dB and it is considered as very good (Yadav, Gangwar, and Singh, 2012).

Moreover, from the Table 2, we infer that our proposed method obtained the highest compression ratio. Flexibility in calculating the threshold value at each individual subband based on subband individual characteristic helps to get a higher compression ratio.

Additionally, our proposed algorithm also shows a good elapse time compared to the previous algorithms. This is because the amount of coefficients is reduced thus decreasing the time taken to complete the task.

CONCLUSIONS

In this paper, we are proposing an algorithm which provide an alternative approach in eliminating wavelet coefficient. This algorithm consider the diversity character of wavelet coefficient in each separated detail subbands.

As can be seen at the result and analysis section, removing the near-zero coefficient at detail subbands can reduce a high amount of wavelet coefficient leading to high compression ratio without degrading the image quality.

For the future work, we will extend our work by developing a new quantization technique for a better compression performance.

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REFERENCES

Baligar, V. P. 2006. Low complexity and high fidelity image compression using fixed threshold method, 176, 664-675. doi:10.1016/j.ins.2004.11.001.

Benzid, R., Marir, F., Boussaad, A. and Benyoucef, M. 2003. Fixed percentage of wavelet coefficients to be zeroed for ECG compression. Electronic Letters, 39(I), 830-831. doi:10.1049/el.

Burak, S., Carlo, G., Bernd, T. and Chris, G. 2001. Medical Image Compression Based on Region of Interest, With Application to Colon CT Images. In 23rd Annual EMBS International Conference (pp. 2453–2456).

Devi, P. S. A. and Mini, M. G. 2012. Compression of Computed Radiographic Images Using Linear Prediction on Wavelet Coefficients. In 2012 International Conference on Advances in Computing and Communications (IEEE Conference Publication) (pp. 130-133). IEEE. doi:10.1109/ICACC.2012.29.

Donoho, D. L. and Johnstone, I. M. 1993. Ideal Spatial Adaptation by Wavelet Shrinkage 1 Introduction, (June 1992).

Janaki, R. 2012. Enhanced ROI (Region of Interest Algorithms) for Medical Image Compression. International Journal of Computer Application, 38(2), 38-44.

K. Sahi, R. 2002. Image Compression Using Wavelet Transform. San Jose State University.

Kofidis, E., Kolokotronis, N., Vassilarakou, A., Theodoridis, S. and Cavouras, D. 1999. Wavelet-based medical image compression. Future Generation Computer Systems, 15(2), 223-243. doi:http://dx.doi.org/10.1016/S0167-739X(98)00066-1

Kourav, A. and Sharma, A. 2014. Comparative Analysis of Wavelet Transform. In IEEE International Conference on Communications and Signal Processing (ICCSP) (pp. 414-418).

Loganathan, R. and Kumaraswamy, Y. S. 2013. Active Contour Based Medical Image Segmentation and Compression Using Biorthogonal Wavelet and Embedded Zerotree. Indian Journal Science and Technology, 6(April), 4390-4395.

Md Taujuddin, N. S. A. and Ibrahim, R. 2014. Medical Image Compression by using Threshold Predicting Wavelet-Based Algorithm. Lect. Notes Electrical Eng, Advance Computer and Communication Technology, Springer, 315, 755-765.

Said, A., Pearlman, W. A., and Member, S. 1996. A New, Fast, and Efficient Image Codec Based on Set Partitioning in Hierarchical Trees, 6(3).

Sánchez, L. E. U., Meana, H. M. P., Miyatake, M. N., Santa, A., No, A., San, C., … Coyoacán, D. 2004. Wavelet Image Compression Using Universal Coefficients Matrix Detail Estimation. IEEE Computer Society.

Shapiro, J. M. 1993. Embedded Image Coding Using Zerotrees of Wavelet Coefficients. IEEE Transactions on Image Processing, 41(92).

Subramanya, S. 2001. Image compression. IEEE Potentials, 20(March), 19-23.

Taujuddin, N. S. A., Ibrahim, R. and Sari, S. 2015. Progressive Pixel-to-Pixel Evaluation to Obtain the Hard and Smooth Region for Image Compression. IEEE Computer Society (6th International Conference on Intelligent Systems, Modelling and Simulation), 102-106. doi:10.1109/ISMS.2015.56.

Walker, J. S. 2000. Lossy image codec based on adaptively scanned wavelet difference reduction. Optical Engineering, 39(7), 1891. doi:10.1117/1.602573.

Wong, S., Zaremba, L., Gooden, D. and Huang, H. K. 1995. Radiologic image compression-a review. Proceedings of the IEEE, 83(2), 194-219. doi:10.1109/5.364466.

Yadav, R. K., Gangwar, S. P. and Singh, H. V. 2012. Study and analysis of wavelet based image compression techniques. International Journal of Engineering, Science and Technology. 4(1), 1-7.