THRESHOLD ESTIMATION BY ADAPTING STANDARD DEVIATION AT WAVELET DETAILS SUBBANDS FOR IMAGE COMPRESSION

N. S. A. M. Taujuddin[1], Rosziati Ibrahim[2] and Suhaila Sari[1]
[1]Faculty of Electrical and Electronic Engineering, Malaysia
[2]Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia
E-Mail: shahidah@uthm.edu.my

ABSTRACT

In this paper, a new algorithm using wavelet properties to compress an image is proposed. This algorithm concern on reducing the wavelet coefficients produced by the Discrete Wavelet Transform (DWT) process. The proposed algorithm start with calculating the threshold value by using the proposed threshold value estimator at wavelet detail subbands (Diagonal, Vertical and Horizontal subband). This proposed algorithm will estimate the suitable threshold value for each individual subband. The calculated threshold values are then applied to its' respective subband. The coefficient with a lower value than the calculated threshold will be discarded while the rest are retained. The novelty of the proposed method is it use the principle of the standard deviation method of deriving the threshold value estimator equation. Experiments show that the proposed method can effectively remove a large amount of unnecessary wavelet coefficient with a higher Peak Signal to Noise Ratio (PSNR) and compression ratio as well as shorter elapse time.

Keywords: discrete wavelet transform, wavelet coefficients.

INTRODUCTION

Wavelet-based image compression techniques have raised interest amongst the image processing community (Vetterli 2001). Beside compression, wavelet also widely been used in noise reduction, detection of microcalcifications, image analysis and image enhancement. Wavelets have offered a great compression ratio without harming the image quality and it became a solemn challenger to Discrete Cosine Transform (DCT) (Bruckmann & Uhl 2000).

Wavelet is well known because of its energy compactness in the frequency domain. Besides, the multiresolution analysis (MRA) offered by wavelet is providing a much higher compression ratio at the same time preserving good image quality (Abirami *et al.* 2013). In addition, wavelet-based compression scheme gives the most excellent rate-distortion performance.

Wavelet-based algorithm has become a pioneering technology in image compression because of its specialty in multi-resolution representation (Yannan *et al.* 2013). Besides, it offers a great reconstruction image providing a promising new ideas and intuitions for image compression (Kourav & Sharma 2014).

RELATED WORK

Some of the common Wavelet methods used in image compression are Embedded Zerotree Wavelet (EZW) and Set Partitioning in Hierarchical Trees (SPHIT). While the extended versions that already been well accepted in committee are Wavelet Different Reduction (WDR) and Adaptive Scanned Wavelet Different Reduction (ASWDR). These algorithms are amongst the prominent compression algorithm that offer the lowest error per compression rate with highest perceptual quality image conveyed (Md Taujuddin & Ibrahim 2014)

This paper will focus on the algorithm of these four (4) wavelet-based compression algorithm. We will take a look on the algorithm steps on each method to see its' evolution before we propose our own.

Embedded zerotree wavelet (EZW)

EZW was first introduce by Shapiro in (Shapiro 1993). The EZW uses 'parent-child' dependencies between subband coefficients at the same spatial location. It generates encoded bits in specific order of importance. It finds the largest coefficient magnitude in 8 x 8 fixed block size image. Then initial threshold is chosen based on the coefficient interval. Every single value of the pixel is then examined in the first dominant pass to determine the sign and the reconstruction value. It continues with first subordinate pass and second dominant pass with new threshold value to get more finer reconstructed magnitude value.

The following is the step for EZW encoding:

Step 1: *Initialize.*
Choose initial threshold, T = T0, such that all transform values satisfy $|w(m)| < T0$ and at least one transform value satisfies $|w(m)| \geq T0/2$.
Step 2: *Update threshold.*
Let $Tk = T_{k-1}/2$.
Step 3: *Significance pass.*
Scan through insignificant values using a baseline algorithm scans order. Test each value w(m) as follows:
If $|w(m)| \geq Tk$, *then Output sign of* $w(m)$
Set $wQ(m) = Tk$
Else if $|w(m)| < Tk$ *then Let* $wQ(m)$ *retain its initial value of* 0.
Step 4: *Refinement pass.*
Scan through significant values found with higher threshold values Tj , for j<k (if k = 1 skip this step). For each significant value w(m), do the following:
If $|w(m)| \in (wQ(m), wQ(m)+Tk)$, *then Output bit 0*
Else if $|w(m)| \in (wQ(m)+Tk, wQ(m)+2Tk)$, *then Output bit 1*
Replace value of $wQ(m)$ *by* $wQ(m)+Tk$.
Step 5: *Loop.* Repeat steps 2 through 4.

Set Partitioning in hierarchical trees (SPHIT)

SPHIT algorithm is an extension of the EZW algorithm and proposed by Said and Pearlman (Said *et al.* 1996). The difference between SPHIT and EZW is the way trees of coefficients are portioned and sorted. It significantly improved the performance of its predecessor by changing the way subsets of coefficients are partitioned and how refinement information is conveyed.

It uses SQuare Partitioning (SQP) method for encoding the significance maps, where it encodes the position of significant coefficients in wavelet image via a hierarchical structure of squares that group the insignificant coefficient in a block of changeable width (Schelkens *et al.* 1999).

The SPIHT encoding is defined as follows:

Step 1: *Initialize.*
Choose initial threshold T0 such that all transform values satisfy |w(m)| <T0 and at least one value satisfies |w(m)|≥ T0/2. Set LIP equal to H, set LSPequal to ∅, and set LISequal to all the indices in H that have descendants (assigning them all type D).
Step 2: *Update threshold.*
Let Tk = Tk−1/2.
Step 3: *Sorting pass.*
Proceed as follows:
For each m in LIP do:
Output Sk[m]
If Sk[m]= 1 then
Move m to end of LSP
Output sign of w(m); set wQ(m) = Tk
Continue until end of LIP
For each m in LIS do:
If m is of type D then
Output Sk[D(m)]
If Sk[D(m)]= 1 then
For each n ∈ C(m) do:
Output Sk[n]
If Sk[n]= 1 then
Append n to LSP
Output sign of w(n); set wQ(n) = Tk
Else If Sk[n]= 0 then
Append n to LIP
If G(m) ≠ ∅ then
Move m to end of LIS as type G
Else
Remove m from LIS
Else If m is of type G then
Output Sk[G(m)]
If Sk[G(m)]= 1 then
Append C(m) to LIS, all type D indices
Remove m from LIS
Continue until end of LIS
Notice that the set LIS can undergo many changes during this procedure, it typically does not remain fixed throughout.
Step 4: *Refinement pass.*
Scan through indices m in LSP found with higher threshold values Tj , forj<k(if k = 1 skip this step). For each value (m), do the following:
If |w(m)|∈(wQ(m),wQ(m)+Tk), then
Output bit 0
Else if |w(m)|∈(wQ(m)+Tk,wQ(m)+2Tk), then
Output bit 1
Replace value of wQ(m) by wQ(m)+Tk .
Step 5: *Loop.*
Repeat steps 2 through 4.

Wavelet different reduction (WDR)

One of the disadvantages of SPHIT is it indirectly locates the position of significant coefficients. This feature makes the process of regionally-based compression harder because the exact position of the significant coefficients cannot be determined accurately.

So, the Wavelet Difference Reduction (WDR) was introduced by (Tian & Wells 1998). The difference between WDR with the previous EZW and SPHIT is the way it encodes the position of the significant wavelet transform value. WDR is used to ease the transmission over small bandwidth by generating an embedded bit stream.

It consists of 3 basic steps: Discrete Wavelet Transform, Differential Coding and Binary coding. Significant transform value is indexed to facilitate Region of Interest (ROI) and compression process.

WDR follows the same step as another bit plane encoding procedure with modification on significant pass step.

Step 3: *Significance pass.*
Perform the following procedure on the insignificant indices in the baseline scan order:
Initialize step-counter C = 0
Let Cold = 0
Do
Get next insignificant index m
Increment step-counter C by 1
If |w(m)|≥ Tk then
Output sign w(m) and set wQ(m) = Tk
Move m to end of sequence of significant indices
Let n = C −Cold
Set Cold = C
If n> 1 then
Output reduced binary expansion of n
Else if |w(m)| <Tk then
Let wQ(m) retain its initial value of 0.
Loop until end of insignificant indices
Output end-marker

The WDR produces a superior image at a high compression ratio too.

Adaptive scanned wavelet different reduction (ASWDR)

ASWDR is the enhanced version of WDR with the new scanning orders in intention to reduce the length of symbol string for encoding the distances. The ASWDR method is well described in (Walker 2000). The modification of ASWDR compared to WDR is only the ASWDR improve the scanning order of the WDR in predicting the new significant value to get higher performance.

In conjunction, the ASWDR produce more significant value compared to WDR because of its better predictive scheme. The significant pass and refinement pass of ASWDR is same as WDR but it enhances with insertion of a step that create a new scanning order.

The advantage of ASWDR is can protect the details at low bit rates and it was beneficial for medical imaging.

The steps for ASWDR encoding are:

Step 1: *Initialize.*
Choose initial threshold, T = T0, such that all transform values satisfy |w(m)| <T0 and at least one transform value satisfies |w(m)|≥ T0/2. Set the initial scan order to be the baseline scan order.
Step 2: *Update threshold.*
Let $Tk = T_{k-1}/2$.
Step 3: *Significance pass.*
Perform the following procedure on the insignificant indices in the scan order:
Initialize step-counter C = 0
Let $C_{old} = 0$
Do
Get next insignificant index m
Increment step-counter C by 1
If |w(m)|≥ Tk then
Output sign w(m) and set wQ(m) = Tk
Move m to end of sequence of significant indices
Let $n = C - C_{old}$
Set $C_{old} = C$
If n> 1 then
Output reduced binary expansion of n
Else if |w(m)| <Tk then
Let wQ(m) retain its initial value of 0.
Loop until end of insignificant indices
Output end-marker as per WDR Step 3
Step 4: *Refinement pass.*
Scan through significant values found with higher threshold values Tj , for j<k (if k = 1 skip this step). For each significant value w(m), do the following:
If |w(m)|∈(wQ(m),wQ(m)+Tk), then
Output bit 0
Else if |w(m)|∈(wQ(m)+Tk,wQ(m)+2Tk), then
Output bit 1
Replace value of wQ(m) by wQ(m)+Tk .
Step 5: *Create new scan order.*

For the highest-scale level (the one containing the all-lowpass subband), use the indices of the remaining insignificant values as the scan order at that level. Use the scan order at level j to create the newscan order at level j−1 as follows. The first part of the newscan order at level j −1 consists of the insignificant children of the significant values at level j. The second part of the new scan order at level j − 1 consists of the insignificant children of the insignificant values at level j. Use this new scan order for level j −1 to create the new scan order at level j −2, until all levels are exhausted.
Step 6: *Loop.*
Repeat steps 2 through 5.

To sum up, in the previous methods the initial threshold value T0, is initialized by choosing randomly the wavelet coefficient value, w(m) that satisfies |w(m)|<T0, and at least one value satisfy |w(m)|≥ T0/2. This value is then reduced by half (T0/2) for each consequent loop. This approach is very simple and low computational cost. However, these methods are just generating good threshold value for the high correlation natural image. This is because the 'parent-child' concept is just concerning on eliminating the insignificant value based on their association only.

On the other hand, this approach accommodates all subband as equal, leaving the different features of wavelet coefficient unexploited. Hence, here this project proposes an alternative approach that considering the diverse character of wavelet coefficient subsequently in each separated detail subband. Detail subbands consist of Diagonal, Vertical and Horizontal subband.

PROPOSED ALGORITHM

The proposed method introduces a new technique that replaces the initialization step with our own threshold estimation. It also eliminates the updating threshold procedure that generates updated threshold for each loop.

The proposed method is firstly specifies the threshold value at each subband by calculating its own threshold at each respective details subband. The new threshold value is calculated by considering the dispersion of the wavelet coefficient value in each single subband.

In constructing new threshold for each subband, we use the standard deviation to measure the distribution of wavelet coefficient value. If the value of standard deviation is low, it shows that most of the wavelet coefficient value concentrates on certain value. Throughout the experiment done, we found that most of the images have a near zero mean value (Refer Table 1). Whereas, higher standard deviation value shows that the wavelet coefficient value disperse at a wider range of value.

One of the advantages of standard deviation is it produced a value that is in the similar unit as used in wavelet coefficient. Besides, standard deviation also can be a good estimator when the sample is more than 75 and it increases its' perfection as the number of samples is increased. So, standard deviation is perfect choice to estimate the coefficient dispersion in each single subband since an image can generate up to 262144 wavelet coefficient value for a 512 x 512 image.

As can be seen in the Table 1, the standard deviation and mean value for approximate subband is very high. This is an indication that the value of the wavelet coefficients is scattered in a very diverse range in its

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subband. Besides, it is also carries a large amount of significant coefficients. So, compression at this subband is not a perfect solution as it may harm the image quality. Plus, the compression ratio is not significantly decreased because only a small amount of coefficients is able to be retrieved.

However, a more compact wavelet coefficient representation can be seen on 3 details subband, the horizontal, vertical and diagonal subband. The mean value of the detail subbands relies on around zero value. While the standard deviation value is low, so it means that most of the wavelet coefficient have the value near zero too. The higher coefficient values in details subband are actually carrying the significant value (usually appear as white representation in edgemap). Most of them also representing the edge of an object in an image.

Table-1. The significant coefficients, standard deviation and mean value for test image.

Image	Subband	Wavelet Coefficients	Standard Deviation	Mean
Barbara	Approximate	291600	52.0756	117.3941
	Horizontal	262144	4.2886	0.000289
	Vertical	262144	7.1493	0.001
	Diagonal	262144	5.9303	8.97E-06
Cameraman	Approximate	291600	61.2227	118.3147
	Horizontal	262144	4.9974	0.0011
	Vertical	262144	7.007	0.000384
	Diagonal	262144	2.408	1.96E-05
Lena	Approximate	291600	47.0973	124.0468
	Horizontal	262144	3.4745	0.000487
	Vertical	262144	5.537	0.00021
	Diagonal	262144	2.7679	8.24E-06

So, by manipulating the near zero coefficient at detail subband, it can reduce a high amount of wavelet coefficient leading to high compression ratio without degrading the image quality.

Our proposed algorithm consists of the following steps:

Step 1: *Transform process.*
Apply Discrete Wavelet Transform on the original image.
Step 2: *Initialize.*
Calculate the threshold λ_D , λ_V , λ_H at details subbands (diagonal, vertical and horizontal) respectively by adapting the standard deviation concept in wavelet coefficients.
Step 3: *Significance pass.*
Scan through insignificant values using a baseline algorithm scans order. Test each coefficient value, w(m), at each subband as follows:
Diagonal subband
If $|w(m)| \geq \lambda_D$, *then retain the w(m) value*
Else if $|w(m)| < \lambda_D$ *then change the w(m) value to 0 .*
Vertical subband
If $|w(m)| \geq \lambda_V$, *then retain the w(m) value*
Else if $|w(m)| < \lambda_V$ *then change the w(m) value to 0 .*
Horizontal subband
If $|w(m)| \geq \lambda_H$, *then retain the w(m) value*
Else if $|w(m)| < \lambda_H$ *then change the w(m) value to 0*
Step 4: R*efinement pass.*
Scan through significant value and make modifications.
Step 5: *Loop.* Repeat steps 2 through 4 for each individual detail subbands.

Details on the threshold (λ_D , λ_V , λ_H) generation can be seen at (Taujuddin *et al.* 2015). Figure 1 shows a block diagram of our algorithm.

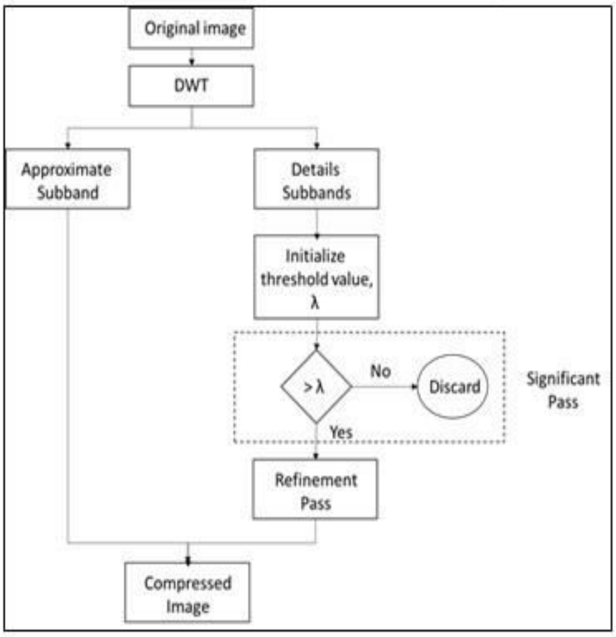

Figure-1. Block diagram of the proposed algorithm.

RESULTS AND ANALYSIS

This experiment is carried out on the MATLAB R2012a platform by using three standard test images, namely Barbara, Cameraman and Lena. The size of the images is 512x512.

To assess the fidelity performance of the proposed algorithm, we compared it with EZW, SPIHT, WDR and ASWDR on compression ratio, and elapse time. A more detailed discussion on this fidelity test can be found at (Kourav & Sharma 2014).

Table-2 shows the objective performance test of Barbara, Cameraman and Lena image using the prominent compression algorithm and the proposed one. From the test done, the images compressed using our proposed method shows a very excellent PSNR (Barbara (42.28dB), Cameraman (47.13dB) and Lena (44.45dB)).

Image with PSNR value more than 40dB, is considered as very good (Yadav *et al.* 2012) and even cannot virtually differentiate between original and reconstructed image by normal human eye observation (J. S. Walker).

For compression ratio test, our proposed algorithm shows a better result for image with large smooth area region (Cameraman and Lena) but average in performance for image with large detail and texture region (Barbara).

While aimed at elapse time test or time taken to complete the task, our proposed method takes the shortest time compared to the average time taken by the EZW, SPIHT, WDR and ASWDR.

Table-2. Objective performance test on prominent wavelet-based compression algorithm and the proposed method.

Image: Barbara			
Algorithms	**PSNR**	**Compression ratio**	**Elapse Time**
EZW	29.72	7.79	16.39
SPIHT	25.29	2.39	6.85
WDR	29.72	**9.24**	7.84
ASWDR	29.72	9.06	11.13
Proposed	**42.28**	5.91	**2.36**
Image: Cameraman			
EZW	33.49	4.02	11.16
SPIHT	28.99	1.30	6.17
WDR	33.49	4.15	6.78
ASWDR	33.49	4.08	10.67
Proposed	**47.13**	**7.12**	**1.44**
Image: Lena			
EZW	32.29	3.99	11.08
SPIHT	28.41	1.25	6.24
WDR	32.29	4.30	5.45
ASWDR	32.29	4.17	9.17
Proposed	**44.45**	**5.89**	**2.06**

CONCLUSIONS

In this paper, we present the idea of reducing the near zero coefficient to for the compression purpose by adaptively using the standard deviation method in thresholding process.

Based on the two quality measures done on four prominent wavelet-based compression algorithms and our proposed algorithm, it shows that our proposed algorithm is a promising one because it provide quite a good compression ratio with superior performance elapse time.

In future, our work will concern on developing a new encoding technique to encode the symbol stream generated by the proposed algorithm to produce a more efficient lossless representation of symbol stream that will lead to a higher compression ratio.

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