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Experimental Approach On Thresholding Using Reverse Biorthogonal Wavelet Decomposition For Eye Image

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***Abstract*—This study focus on compression in wavelet decomposition for security in biometric data. The objectives of this research are two folds: a) to investigate whether compressed human eye image differ with the original eye and b) to obtain the compression ratio values using proposed methods. The experiments have been conducted to explore the application of sparsity-norm balance and sparsity-norm balance square root techniques in wavelet decomposition. The eye image with [320x280] dimension is used through the wavelet 2D tool of Matlab. The results showed that, the percentage of coefficients before compression energy was 99.65% and number of zeros were 97.99%. However, the percentage of energy was 99.97%, increased while the number of zeros was same after compression. Based on our findings, the impact of the compression produces different ratio and with minimal lost after the compression. The future work should imply in artificial intelligent area for protecting biometric data.**

I. INTRODUCTION

The security issues of token-based or knowledge-based authentication systems can be resolved using the biometric authentication systems. This technology helps the system in recognition and detection of human, based on physical and behavioural traits. The biometric data or templates belong only to a person and neither is used by other person, nor forgotten.

Apparently, the biometric templates can be stolen or misuse which creates vulnerability of the biometric authentication system and lead to circumvent the integrity of biometric templates.

The purpose of this study is to investigate whether the compression in human eye provide security to the biometric authentication system. Another objective is to obtain the compression ratio in determining the difference between the original and the compressed human eye image. Here, the wavelet 2D Matlab tool is applied in implementing the experiments.

In the wavelet 2D Matlab, rbio tool or reverse biorthogonal wavelet is used in this research. It is because rbio is a kind of wavelet which is correlated to a wavelet transform. However, it is not essentially orthogonal (or from the same side/area). Using reverse biorthogonal wavelet, gives freedom in designing in any system compare to orthogonal wavelets, for instance, the opportunity in constructing the symmetric wavelet functions. The two functions generated different mutiresolution analyses which are based on two different wavelet functions. Thus, the numbers of coefficients in the scaling sequences may differ. In other words, a set of two different wavelet functions are used to analyse data. A set of symmetric wavelet functions deconstructed data without gaps or overlap. This is to ensure that the deconstruction process is reversible. Moreover, the recovery of the original biometric data is in minimal loss since it is useful based on compression and decompression algorithms. Other than that, the design is more flexible and the threshold values can be measured from different levels.

Two methods of reverse biorthogonal wavelet have been used, which are the sparsity normal balance and sparsity normal balance square root. The sparsity feature in rbio is useful for feature compression and storage optimization.

The sparsity normal balance method is important in estimating an appropriate threshold for an image. It produces the compressed data as a default compared to the original, which is before the compression. In the other hand, the sparsity normal balance square root is vital in obtaining the better results in terms of threshold values, compression ratio and the human perceptibility. This is since the negative value or real numbers have been square root in gaining or actual numbers.

The experiments are undergo in determining whether the compression gives better compression ratio in terms of percentage of energy and number of zeros before and after the compression process. The security of the biometric data (human eye image) in biometrics authentication system is based on energy and number of zeros at certain threshold value.

II. RELATED WORK

In biometric authentication systems, a high security system to govern the data transmission between a sender and a receiver nodes are highly demand[1], [2]. Most systems nowadays involve data to be transferred through wired and wireless channel in the computer networking. Without proper protection mechanism, biometric data can be easily copied, modified, tampered, or forged during transmission. Protecting the integrity, validity and ownership of digital data has become an important issue today[3].

Therefore, a lot of researches have been done to investigate the techniques for making the biometric systems a secured but convenient for user. One of the techniques in improving the security is compression[4–8]. In fact, compression is useful for bandwidth utilization, storage optimization, image file size reduction and increase security protection[9]. The application area of compression in wavelets are medical imaging[10], geographical research[11–13] and security and privacy[8], [14–16]. For example, a genetic algorithm based mapping function has been introduced to embed data in Discrete Wavelet Transform (DWT) coefficients in 4x4 blocks on the cover image.[17]

The compressed image was up to the level where the values of residual coefficients and decomposition of image determine the level of tendency and dispersion[18]. According to [19], the threshold criteria is applied to the coefficients for feature extraction. There are two basic threshold based strategy for signal compression: level-dependent and global thresholding. Both methods are a hard threshold. Another way to maintain the robustness in data is to employed DWT uses down and up sampling which leads to loss of information. Whereas in LWT, there is no down and up sampling as such which increases the CRC values leading to highly robust watermark [20].

The threshold scheme for the compression techniques in wavelet decomposition consists of three fundamental methods which are balance sparsity-normal, balance sparsity-normal square root and remove near 0. In Matlab tool, these compression applications are as in Table I.

TABLE I: THRESHOLDING FOR COMPRESSION

Method	Threshold Scheme
Remove Near 0 Thresholding [21][22]	The remove near 0 is to remove the pixels to zero is resetting the image. With the near-zero thresholding method, it is difficult to determine exactly where the optimal threshold is, since all values of all levels are the same.
Sparsity – Normal Balance Thresholding [23][24][25]	The Normal Balance Thresholding estimated the thresholds values according to level of decompositions. The compressed data is default value as the original.
Sparsity–Normal Balance Square Root Thresholding [26][25]	The Normal Balance Square Root Thresholding produce the sqrt compressed image in making a better performance in terms of compression ratios, thresholds values and human imperceptibility.

III. METHODS

In this study, we only focus on the two methods, excluding the remove near 0. The reason why behind it is, remove near 0 method removed the pixels to zeros which the image became reset. Thus, it is difficult to determine the optimal threshold since all values of thresholds are the same. Therefore, we only applied the balance normal and balance normal square root methods [25].

A. Sparsity-Norm Balance Thresholding

The threshold values and compression ratios are estimated for the human eye image. According to Birgé and Massart strategy,[27] let $a = 1.5$ for compression. These strategies can be viewed as a variant of the fixed form strategy of the wavelet shrinkage. The sparsity parameter is a more than 1, the coefficients are sorted in decreasing order of their absolute value and the noise variance. Three different intervals of choices for the sparsity parameter a, which are HIGH, 2.5, $a < 10$, MEDIUM, $1.5 < a < 2.5$ and LOW, $1 < a < 2$.

The dedicated threshold estimation is set by level 1, 2 and 3. With the near-zero thresholding method, it is hard to determine exactly where the optimal threshold is. Under this heuristic, the successive thresholds are tested and calculate the norm of the spectrum after each threshold. Our goal in calculating the norm of the spectrum is to balance thresholding with loss in image quality.

The metric used to measure loss of image quality is the normal, which actually calculates how much total energy loss after compression [25]. Zero value corresponds to the gray color in the image. In the multiresolution nature of the wavelet decomposition compact the energy in the signal into a small number of wavelet coefficients. The image energy is concentrated in the LL (lower band, low frequency) which contains most of image energy. To find the right balance for each threshold, the normal ratio is calculated from the compression of the original spectrum. When the threshold is 0, the percent number of zeros should be close to 0%, while the percent norm is 100%. However, when the threshold is at 1, it is expected that the percent zeros to be 100%, while the percent at normal is 0%.

Thus, the curves of the two quantities intersect at some point, the global threshold settings to be at this intersection. This method, borrowed from MATLAB's Wavelet Toolbox, is called balanced sparsity norm. In addition, it is recognize that a loss of coefficients at the lower levels of the decomposition (the smaller quadrants in the upper left corner) makes a much greater impact on the quality of the image than the coefficients at higher levels of the decomposition. A solution to this problem is to only decompose the image to a certain level, instead of decomposing the image down to the last pixel. In fact, depending on the recursive depth of the image, one obtains drastically different compression rates. Thus, the image is decomposed only up to the third recursive level, which, performed the decomposition (only up to level 3) and ran the sparsity norm balance routine. In most cases, the threshold seemed to be too high in terms of preserving image quality.

B. Sparsity –Norm Balance Square Root Thresholding

The coefficients need to be reduced in proportion to the calculated threshold, for fixed c and threshold value t the square-root balance sparsity norm threshold is calculated, p (t/c)/c (also from MATLAB's Wavelet Toolbox). In this case, c = 128. In both cases, the square-root balance proves to be the better trades off between image quality and compression rate. Although the balance threshold gives a phenomenal compression rates (better than 1:20 compression), the image quality is sacrificed. Refer to Fig 1(c)(d).

The indicators to measure the compression performance which commonly used are the compression ratio or energy ratio and bit-per-pixel ratio. The compression ratio shows the compressed image is stored using the percentage of the initial storage size. Meanwhile, the bit-per-pixel ratio gives the number of bits required to store one pixel of the image. In this case, we analyze the bit-per-pixel ratio based on the number of zeros percentage, since we can estimates the zero pixel values inside the compressed image of human eye.

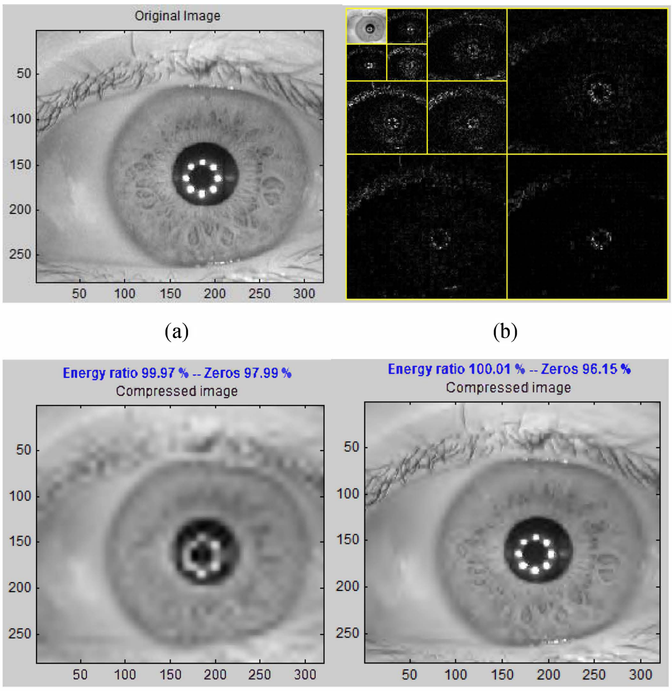
C. Experiment Results and Discussions

In this section, the first three levels of decomposing and eight different wavelet functions of reverse biorthogonal functions was chosen for compression. The experiments have been conducted on CASIA database of 200 human eye images. Using the Matlab 2D tool, the experiments have been conducted in measuring the threshold, compression ratios and zeros ratio percentage. Table I show the results of compressions ratios and zeros ratios, before and after the compression, using the thresholding methods in compression.

TABLE I
THRESHOLDING USING BALANCE SPARSITY NORMAL AND BALANCE SPARSITY NORMAL SQUARE ROOT

Wavelet: rbio DWT Decomposition (1.5)										
Thresholding Method		Balance Sparsity Normal					Balance Sparsity-Normal (sqrt)			
Level (D)	Threshold	Energy (%)		Zeros (%)		Threshold	Energy (%)		Zeros (%)	
		before	after	before	after		Before	after	before	after
1	131.0	99.93	100	75.00	75.00	11.45	99.97	100	72.38	72.38
2	143.1	99.81	100	93.26	93.26	11.96	99.96	100	87.26	87.26
3	470.6	99.65	99.97	97.99	97.99	21.69	99.93	100	94.53	94.53
4	746.5	99.54	99.91	99.29	99.29	27.32	99.94	100	96.15	96.15
5	516.6	99.68	99.95	99.68	99.68	22.73	99.97	100	95.15	95.15
6	586.4	99.79	99.42	99.80	99.80	24.22	99.99	100	95.31	95.31
7	988.6	99.85	98.72	99.85	99.85	31.45	99.99	100	96.30	96.30
8	1884	99.88	96.91	99.88	99.88	43.40	100	100	97.31	97.31

According to Table I, the sparsity balance norm square root method gives 100% energy ratio after the compression compared to sparsity balance norm. Using the method of sparsity balance norm square root, provide better security feature to biometric data. However, the percentage of number of zeros remains the same values. It means, the original data still remained inside the compressed data. If the number of zeros higher or lower in percentage values, after the compression, it means data has been changed or has minimal data loss. Without loss of generality, the compression ratio improved with an increment in the level of decomposition. However the relative improvement is not very significant when the image is decomposed at level 7 and 8.



(a) (b) (c) (d)

Fig. 1. (a) The original eye (b) decomposition at level 3 (rbio wavelet 1.5) according to birgé and massart strategy (c) sparsity nom balance eye after compressed (d) sparsity nom balance square root eye after compressed.

According to Birgé-Massart method [28], this method includes a sparsity parameter a ($1 < a < 5$), which, the default is $a = 1.5$. Note that c is all the detail coefficients of the binned data, $d(j)$ is the detail coefficients at level j and n is the number of bins chosen for the preliminary estimator (binning). Then, these options are defined as follows:

$$max(|c|) \times \frac{\log(n)}{\sqrt{n}} \quad (1)$$

Where (1) is the global thresholdings.

Threshold value is set to *level 1*: ***0.4 x max (|d(j)|)*** **(2)**

Threshold value is set to *level 2*: ***0.8 x max (|d(j)|)*** **(3)**

Threshold value is set to *level 3*: ***a x max (|d(j)|)*** **(4)**

The sparsity can be HIGH (default), MEDIUM and LOW. It shows that it was a growth in threshold values for balance norm square root method, as the level of decomposition increasing. Based on the experiments shows that the high sparsity proven that the compressed biometric data at the default sparsity, which the coefficient is between 1 < a < 5 show the arising graph as well. Refer to Fig 2 and Fig 3.

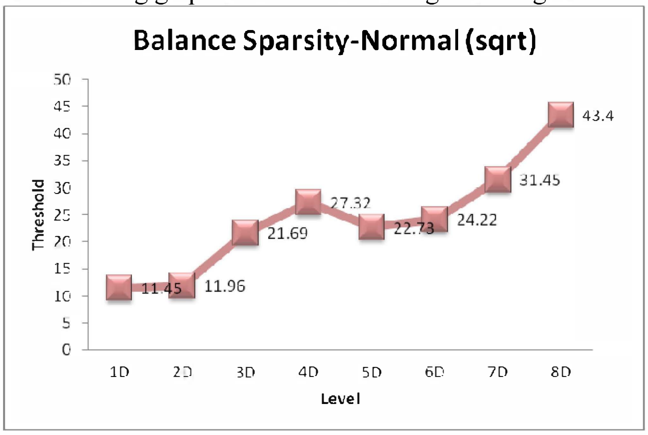


Fig. 2. Comparison between threshold values and level (1 to 8) of wavelet decompositions using sparsity balance norm square root.

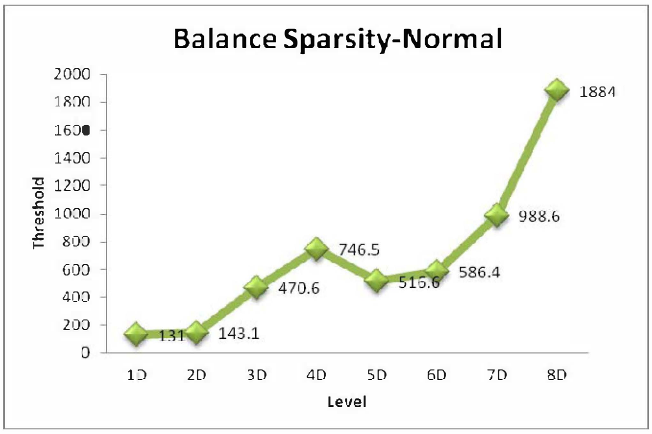


Fig. 3. Comparison between threshold values and level (1 to 8) of wavelet decompositions using sparsity balance norm.

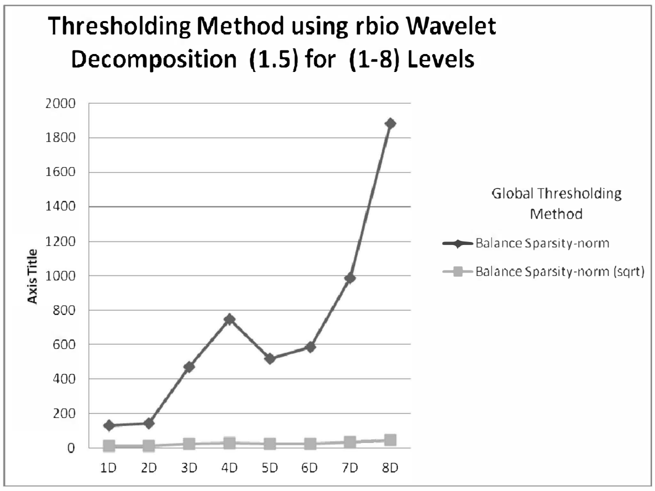


Fig.4. Comparison between thresholding using rbio wavelet decomposition (a = 1.5) values for level (1 to 8) in global settings method.

Fig 4 shows the graph between the balance sparsity normal square root and balance sparsity normal in global thresholding. The significant difference is noticed as the energy loss is less using the balance square root method compared to balance sparsity. The variation is too small since the threshold values are from 0 to 50. Therefore, the graph of square root show slight linear compared to the balance sparsity normal that the value of threshold is huge that is from 0 to 2000. The compression using biorthogonal basis function creates minimal losses especially when consists of significant contrast in biometric eye image. This produce result of data security is remains although compressions and decompressions processes have been done.

The values of thresholds have been identified from the range of set threshold values, decomposition at level 3, 4 and 5 produce image of eye that acceptable to the human vision. Refer Fig 1. (a)(c)(d).

At the same time, the actual bit-per-pixel ratio of the image is smaller in percentage, meaning the compressed image is unnoticed by human vision. From the image perspective, the compressed image is more invisible or data is hidden after the compression process. In addition, the security of the biometric data is greater through the process of compression.

IV. CONCLUSION

In this paper, different eight levels of wavelet in reverse biorthogonal at 1.5, were examined. The experiments showed that rbio wavelets produced best threshold at level 3, 4 and 5 for compression within suitable space due to their properties and applications. Besides approximation of threshold value, the compression ratios were chosen in looking at the percentage of data lost in eye whether maximum or minimum for the sake of security performance. Furthermore, it can be depicted from the experiments that the best number of threshold levels is three, four and five of the decomposition. A set of human eye images from CASIA database is used in the experiments. Future works in conjunction to this paper will concentrate on finding other method in artificial intelligent to secure the biometric data features however remains the important information.

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