Fingerprint Image Compression Using Retain Entergy (RE) And Number of Zeros (NZ): A Multi -Wavelet Approach

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Abstract:
An automatic recognition of people based on fingerprints that the input fingerprint be matched with large number of fingerprints, and these increasing amount fingerprints collected by law enforcement agencies has created enormous problem in storage and transmission. Therefore it is often necessary to compress the image while storing the necessary data for subsequent reconstruction. There are many image compression techniques available at present. Recently the wavelet transform has emerged as a cutting edge technology within the field of image compression. A variety of powerful and sophisticated wavelet based schemes for image compression have been developed and implemented. Due to implementation constraints of scalar wavelets do not possessing the all desirable properties which are needed for better performance in compression. Relatively new class of wavelets called Multiwavelets were introduced and which are able to posses all desirable properties simultaneously. Our objective in this paper is to develop faster, more stronger and healthy compression scheme and to obtain better quality and higher compression ratio through Multiwavelets. In this paper we have done experimental analysis and calculated the Retain Energy (RE) and Number of Zeros (NZ). The results which we have achieved prove that Multiwavelets are superior for Fingerprint images.

Key words: Fingerprint Image compression, Multiwavelet, Wavelet, Retain Energy and Number of Zeros.

Introduction:
Biometric system is an imperative area of research in recent years, authentication and verification of persons by biometric sign. The biometric system contains different signs Fingerprint, Face, Iris, Hand, Pam etc. Out of these signs fingerprint is the oldest and more reliable sign used for identity [David M, L.C>Jain, RNCOS]. The Federal Bureau of Investigation (FBI) deals with a large collection of fingerprints containing more than 200 million cards and this volume is growing at rate of 30,000 to 50,000 new cards per day [G.A. Khuvaja]. Digitization of these cards requires greater storage space, likewise their retrieval and transmission requires larger time. Therefore it is often necessary to compress the image while storing the necessary data for subsequent reconstruction [R.R. Manza, Gornale S. S. et. al]. There are many image compression techniques available, but still there is need to develop faster and more strong and healthy techniques to compress the fingerprints images. Because, main difficulties in developing compression algorithm for fingerprint is the need for preserving the minutiae i.e. ridges endings and bifurcations which are subsequently used in identifications. The performance of existing image coding standard generally degrades at low bit rates because the underlying block

based discrete cosine transform scheme [Rao K.R]. Recently, the wavelet transform with the concept of Multiresolution Analysis (MRA) has emerged as a very powerful tool for image data compression [R.B.Polikar, K.P.Soman, Raghuveer M Rao, C. Valens Martin J Mohlen Kamp, I Daubenchies]. It provides a vehicle for image processing application, because it has ability to take into account Human Visual System (HVS) characteristics, good energy compaction capabilities under transmission and decoding. It is also more robust under transmission and decoding error which results in compression ratio. Over the past few years, a variety of powerful and sophisticated wavelet based schemes for image compression have been developed and implemented.[Subhasis Shaha, Michael B. Martin, S.S. Gornale(journal), R.C. Gonzalaz, S.G. Mallat, S.S. Gornale(Hubli)].

To achieve a high compression rate, it is often necessary to choose the best wavelet filter bank and decomposition level, which will play a crucial role in compressing the images. The selection of wavelet filters plays a crucial part in achieving an effective coding performance, because there is no filter that performs the best for all image[subhasis shar and rao vemuri, S. S. Gornale(journal signal)]. For better performance in image compression, filters used in wavelet transforms should have the property of Orthonormality, Filter length, Vanishing order or moment, Smoothness, Filter magnitude response, Group delay, Decomposition level, Regularity etc.[Bryan E. Usevitch , John D, Wavelt toolbox, satyabrata Rout]. Due to implementation constraints scalar wavelets do not satisfy all these properties simultaneously [Jo Yew Than]. Relatively new class of wavelets called Multiwavelets holds promise in obviating some of the limitations of wavelet by possessing more than one scale filters. Multiwavelets have several advantages over scalar wavelets such features as short support, orhtogonality, symmetry, and high number of vanishing moments which are known to be important in image processing[Michael B martin(2000), Micheal martin(2001), S rout(2002), Mariniatia(2000), kai Bao(2001), Micheal martin(1999), A.P.Began(2001), L.R.iyer(2001), sudhakar R]. Multiwavelets can achieve better level of performance than scalar wavelets with similar computational complexity.

2 Wavelets (W) and Multiwavelets (MW) for Image compression:

2.1 Wavelets (W):

The theory of Wavelets starts with the concepts of Multi Resolution Analysis (MRA) [8], [9], [10], [11], [12], [13], [14], [15] has emerged as very powerful tool for data compression. It provides a vehicle for image processing applications, because it has ability to take into account Human Visual System (HVS) characteristics, good energy compaction capabilities under transmission & decoding. It is also more robust under transmission & decoding error, which results in a high compression ratio. In addition to these, wavelet transforms compression provides a superior image quality at low bit rates [9], since there is no need of blocking the image. The Practical implementation of wavelet compression schemes is very similar to that of subband coding schemes. As in the case of subband coding, we decompose the signal (analyze) using filter banks. The outputs of the filter banks are downsampled, quantized, and encoded. The decoder decodes the coded representation, upsamples, and recomposes the signal. [16],[17].

2.2 Wavelet properties:

To achieve a high compression rate, it is often necessary to choose the best wavelet filter bank and decomposition level, which will play a crucial role in compressing the images. The selection of wavelet filters plays a crucial part in achieving an effective coding performance, because there is no filter that performs the best for all images [20]. The Current Compression system uses the biorthogonal wavelet filters instead of orthogonal, because; orthogonal filters have a property of energy preservation, whereas biorthogonal filters lack it [21],[22]. The choice of optimal wavelets has several criteria. The main criteria are: Orthonormality, Filter Length, Vanishing order or moment, Smoothness, Filter magnitude response, Group delay, Decomposition level, Regularity, etc., and these are discussed in [21],[22],[23],[24]. Orthogonal Filters lead to orthogonal wavelet basis functions; therefore the resulting wavelet transform is energy-preserving; this implies that the Mean Square Error (MSE) introduced during the quantization of the DWT coefficients is equal to the MSE in the reconstructed signal. In biorthogonal wavelet, the basis functions are not orthogonal; therefore they do not preserve the energy but conserve it. The efficiency of a transform depends on how much energy compaction is provided by the transform; Wavelet Filter can be used to analyze or decompose signals and images, which is called Decomposition. The same components can be assembled back into the original signal without loss of information, which is called reconstruction or synthesis. Shorter synthesis basis functions are desirable for minimizing distortion that affects the subjective quality of the image. Longer filters are responsible for ringing noise in the reconstructed image at low bit rates [24]. Each wavelet family is parameterized by an integer N called the filter order, which is proportional to the length of the filter. The length of the filter is related to the degree of the smoothness of the wavelet and can affect the coding performance. This relation is different for different wavelet families and non-smoothness basis function introduces artificial discontinuities, which are reflected as spurious artifacts in the reconstructed images. Higher filter order gives more energy and increases the complexity of calculating the DWT coefficients, while lower order preserves the energy. i.e. it preserves the important edge information. Therefore, we must take care of wavelets in image compression application concerning good balance between filter orders, degree of smoothness and, computational complexity. These properties depend on the image contents. Vanishing order is the measure of compaction property of the wavelet and it corresponds to the number of zeros in the LL sub band [24],[25].

2.3 Motivation behind Multiwavelets

Algorithms based on wavelets have been shown to work well in image compression. For better performance in image compression, wavelets transforms requires filters that combines a number of desirable properties such as orthogonality, Symmetry. However, the design possibilities for wavelets are limited because they cannot simultaneously posses all the desirable properties. In contrast to the limitations of wavelets, Multiwavelets are able to posses the best for all these properties simultaneously due to the extra freedom in the design of multi-filters. Another desirable feature of any transform used in image compression is the amount of energy compaction achieved. A filter with good energy compaction property can decorrelate a fairly uniform input signal into a small number of scaling coefficients containing most of the energy and large number of sparse wavelet coefficients. This becomes important factor during quantization. Therefore better performance is obtained when the wavelet coefficients have values clustered about the zero with little variance to avoid as much as quantization noise as possible. Thus Multiwavelets have the potential to offer better reconstructive quality of the same bit rate and can achieve better level of performance than the wavelets with a similar computational complexity.[sudhakar R, Michael b martin(2001).

2.3.1 Multiwavelets (MW):

Multiwavelets are similar to the wavelets but have some important difference i.e. Multiwavelets are characterized with several scaling functions and associated wavelet functions. Let the scaling functions be denoted in vector form as $\Phi(t) =[\varphi 1(t), \varphi 2(t), \ , \varphi L(t)]^T$, where $\Phi(t)$ is called the multiscaling function, T denotes the vector transpose and $\varphi j(t)$ is the jth scaling function. Likewise, let the wavelets be denoted as $\Psi(t) = [\psi 1(t), \psi 2(t), \ldots, \psi L(t)]^T$, where $\psi j(t)$ is the jth wavelet function. Then, the dilation and wavelet equations for Multiwavelets take the following forms, respectively:

$\Phi(t) = \sqrt{2}\sum H[k]\Phi(2t - k)$,

$\Psi(t) =\sqrt{2}\sum G[k]\Phi(2t - k)$…………(1)

The low-pass filter H and the high-pass filters G are N × N matrix filters, instead of scalars. In theory, N could be as large as possible, but in practice it is usually chosen to be two. This degree freedom can be used to incorporate useful properties of the Multiwavelet such as orthogonality, symmetry, and high order approximation.[Michael B. Martin(2000)] For single scaling and wavelet functions extends to the matrix version. The resulting two channels, 2 × 2 matrix filter bank operates on two input data streams, filtering them into four output streams. Each of these streams is then downsampled by a factor of two. This procedure is as shown in Figure-1

2.3.2. Implementation of Multiwavelets.

In scalar wavelet, during the single level of decomposition the image data is replaced with four blocks corresponding to the sub bands representing either low-pass or high-pass filtering in each direction (Horizontal, Vertical, Diagonal and Approximation). Multiwavelets have two channels, so that there will be two sets of scaling and two sets of wavelets coefficients. 2-D Multiwavelet decomposition has the 16 subband intermediate image (single level decomposition) as shown in figure-2.

L1L1	L1L2	L1H1	L1H2
L2L1	L2L2	L2H1	L2H2
H1L1	H1L2	H1H1	H1H2
H2L1	H2L2	H2H1	H2H2

Figure-2: Single Level Multiwavelet Decomposition

As Scalar wavelet transforms give a single quarter sized low-pass subband from the original larger subband. In Multiwavelet, the multilevel decompositions are performed in the same. Multiwavelet iterates on the low-pass coefficients from the previous decomposition; the quarter image of "Low-pass coefficients is actually a 2x2 sub bands.

L1L1	L1L2
L2L1	L2L2

The next step decomposes the “Low-Low-Pass” sub matrix in the similar manner which gives the Second level of Decomposition and as shown in Figure-3.. An N number of Decomposition of a 2D image will produce the 4(3N+1) subband (sub images)[Hai Hui]

<table>
<tr><td>L1L1</td><td>L1L2</td><td>L1H1</td><td>L1H2</td><td rowspan="2">L1H1</td><td rowspan="2">L1H2</td></tr>
<tr><td>L2L1</td><td>L2L2</td><td>L2H1</td><td>L2H2</td></tr>
<tr><td>H1L1</td><td>H1L2</td><td>H1H1</td><td>H1H2</td><td rowspan="2">L2H1</td><td rowspan="2">L2H2</td></tr>
<tr><td>H2L1</td><td>H2L2</td><td>H2H1</td><td>H2H2</td></tr>
<tr><td colspan="2">H1L1</td><td colspan="2">H1L2</td><td>H1H1</td><td>H1H2</td></tr>
<tr><td colspan="2">H2L1</td><td colspan="2">H2L2</td><td>H2H1</td><td>H2H2</td></tr>
</table>

Figure-3: Second Level Multiwavelet Decomposition

3. Implementation:

The Multiwavelet decomposition of source image is computed at different level (or scale). The filters which we have used in this are “GHM” pair of filters. The source image is decomposed into subbands which can be treated as sub images. At each level of decomposition 16 subimages and they can be divided into 4 blocks as shown in figure-2. The Low-Low (LL) subband block shows the image’s approximate (this block includes four subimages). The Low-High (LH) subband block, High-Low (HL) and High-High (HH) block shows the detail part of the image in Horizontal (H), Vertical (V) and Diagonal (D) directions respectively. To get the next level again decompose the approximate image i.e. Low-Low (LL) subbands and son on. The approximation subimages shows the general trend of pixel values, and three detail subimages show the Vertical, Horizontal and Diagonal details or changes in the images. If these details are very small, 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 threshold. The greater the number of zeros the greater the compression ratio. The amount of information retained by an image after compression and decompression is known as the retained energy and this is proportional to the sum of the square of the pixel values. If the energy retained is100% 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 details have not been changed. If any values are changed, then energy will be lost; this is known as lossy compression. Ideally, during compression, the number of zeros and the energy retention should be as high as possible. However, as more zeroes are obtained, more energy is lost; so a balance between the two needs to be found [18], [19]. Retain Energy (RE) and Number of Zeros (NZ) are calculated by following formulas:

$$RE = \frac{100 * (\mathrm{Vn}\ (\mathrm{CCD},2))^2}{(\mathrm{Vn}(\mathit{origional\ Signal}))^2}$$

and

$$NZ = \frac{100 * (\mathrm{ZCD})}{No.of\ \ coeificients}$$

Where, Vn is the Vector norm, CCD is the coefficients of the current decomposition and ZCD is the Number of zeros of the current decomposition.

4. Results and Discussion:

In Table1 Retain Energy and Number of Zeros are determined by default threshold value for Fingerprint image of size 256x256 taken from FVC2002 Database. The GHM pair of filters are used to decompose the original image and than applied Daubechies (db1 to db5), Symlet (sym2 to sym6) and coiflet (coif1 to coif5) Wavelets to get the Retain Energy and Number of Zeros from Multiwavelets decomposed approximation, with 1 to 2 decomposition level are applied on the image and calculated the Retain energy and number of zeros. In daubechies(db1 to db5), symlet(sym2 to sym6) and in coiflet(coif1 to coif5). The best results are found at level 2 in db5,sym6 and coif5 respectively. Among all these the highest compression is found in coif5 at level 2. Through this work, we have observed that if we increase the order and level of wavelets in Multiwavelets the compression ratio is increases. It is also observed that with increasing of level and order the compression ratio increase, but compressed image get blurred i.e. if the compression ratio increases the quality of the compressed image decreases and vice versa.

5. CONCLUSION:

The performance is generally depends on the image characteristics. For the images mostly low frequency contents (ordinary still images) scalar wavelets gives better performance. However the Multiwavelets appear to excel at preserving frequency content. As fingerprints are normally high frequency patterns. In this paper, we have highlighted the compression ratio for Multiwavelets We have focused how the compression ratio can increases by selecting appropriate level of decomposition. The compression ratio of fingerprint image is determined by considering the Retain Energy and Number of Zeros. We have achieved better compression ratio in Multiwavelets at level 2. If we increase the level of decomposition the compression increases but compressed image get blurred. It is concluded that the compression ratio is depends on the type of image and type of transforms because, there is no filter that performs the best for all images. Hence, there is always necessary to select the appropriate threshold value to get higher compression and the minimum loss of image contents.

Table 1: Shows the Retain Energy (RE) and Number of Zeros (NZ) for Fingerprint image (256x256)

Wavelet Name	Level 1		Level 2	
	Retain Energy (RE)	**No. of Zeros (NZ)**	**Retain Energy (RE)**	**No. of Zeros (NZ)**
Db1	99.997	58.9405	99.9939	42.1692
Db2	99.999	48.5514	99.9938	46.9938
Db3	99.9999	47.8751	99.9938	50.5447
Db4	99.9999	47.5108	99.9940	52.0737
Db5	99.9999	46.9413	99.9940	52.9302
Sym2	99.9999	48.5514	99.9938	46.4327
Sym3	99.9999	47.8751	99.9938	50.5447
Sym4	99.9998	48.3215	99.9936	52.4267
Sym5	99.9998	47.8389	99.9936	53.9668
Sym6	99.9998	47.9358	99.9937	54.5547
Coif1	99.9999	48.2019	99.9938	47.0738
Coif2	99.9999	48.1370	99.9940	52.5859
Coif3	99.9999	47.8312	99.9943	55.2876
Coif4	99.9999	47,4757	99.9947	55.2876
Coif5	99.9999	47.4244	99.9949	55.6705

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