Fingerprint Compression Using Multiwavelets

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Abstract—Large volumes of fingerprints are collected and stored every day in a wide range of applications, including forensics, access control etc. It is evident from the database of Federal Bureau of Investigation (FBI) which contains more than 70 million finger prints. Compression of this database is very important because of this high Volume. The performance of existing image coding standards generally degrades at low bit-rates because of the underlying block based Discrete Cosine Transform (DCT) scheme. Over the past decade, the success of wavelets in solving many different problems has contributed to its unprecedented popularity. Due to implementation constraints scalar wavelets do not posses all the properties which are needed for better performance in compression. New class of wavelets called 'Multiwavelets' which posses more than one scaling filters overcomes this problem. The objective of this paper is to develop an efficient compression scheme and to obtain better quality and higher compression ratio through multiwavelet transform and embedded coding of multiwavelet coefficients through Set Partitioning In Hierarchical Trees algorithm (SPIHT) algorithm. A comparison of the best known multiwavelets is made to the best known scalar wavelets. Both quantitative and qualitative measures of performance are examined for Fingerprints.

Keywords—Mutiwavelet, Modified SPIHT Algorithm, SPIHT, Wavelet.

I. INTRODUCTION

FINGERPRINTS are the ridge and furrow patterns on the tip of the finger and are used for personal identification of the people [1]. An automatic recognition of people based on fingerprints requires that the input fingerprint be matched with a large number of finger prints. Due to large volume of data in a database consumes more amount of memory. Hence an effective method should be adopted to utilize the memory effectively by storing the Finger prints in a compressed format. Data compression algorithms are used in the standards such as JPEG and MPEG, to reduce the number of bits required for representing an image or a video sequence, i.e., compression is

necessary and essential method for creating image files with manageable and transmittable sizes. Image compression is now essential for applications such as transmission and storage in data bases. For still image compression, the `Joint Photographic Experts Group' or JPEG [1] standard has been established by International Standards Organization (ISO) and International Electro-Technical Commission (IEC). The performance of these coders generally degrades at low bit-rates mainly because of the underlying block-based Discrete Cosine Transform (DCT) [2] scheme. More recently, the wavelet transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. Over the past few years, a variety of powerful and sophisticated wavelet-based schemes [3],[4] for image compression, have been developed and implemented.. For better performance in compression, filters used in wavelet transforms should have the property of orthogonality, symmetry, short support and higher approximation order. Due to implementation constraints scalar wavelets do not satisfy all these properties simultaneously [5],[6]. New class of wavelets called 'Multiwavelets' which posses more than one scaling filters [7] overcomes this problem. Thus multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. Multiwavelets can achieve better level of performance than scalar wavelets with similar computational complexity.

This paper is organized as follows: Section II highlights some key points on Multiwavelets. Section III provides the Motivation for going into Multiwavelets for Image Compression. Section IV presents the Filter Bank Approach for Multiwavelets. Section V discusses the Coding of Multi wavelet Coefficients using Modified SPIHT Results and discussions are presented in section VI and finally conclusions are drawn in the section VII.

II. MULTIWAVELETS

Multiwavelets are defined using several wavelets with several scaling functions [7]. Multiwavelets have several advantages in comparison with scalar wavelet [8]. The features such as compact support, Orthogonality, symmetry, and high order approximation are known to be important in signal processing. A scalar wavelet can not possess all these properties at the same time [9]. On the other hand, a multiwavelet system can *s*imultaneously provide perfect reconstruction while preserving length (Orthogonality), good

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performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments) [10]. Thus multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets.

The study of multiwavelets was initiated by Goodman, Lee and Tang. Then Goodman and Lee discovered the characterization of scaling functions wavelets. Jia constructed a class of continuous orthogonal double wavelets with symmetry, short support, and Orthogonality. The special case of Multiwavelets with multiplicity 2 and support (0, 2), was studied by Chui and Lian. When a multiresolution analysis is generated using multiple scaling functions and wavelet functions, it gives rise to the notion of multiwavelets [5]. A multiwavelet with r scaling functions and r wavelet functions is said to have multiplicity r. When r = 1, one scaling function and one wavelet function, the multiwavelet system reduces to the scalar wavelet system. Multiwavelets have two or more scaling functions and wavelet functions. For notational difference the set of scaling functions can be written using the vector notation $\Phi(t) = [\Phi_1(t) \quad \Phi_2(t) \ldots . \Phi_r(t)]^T$, where $\Phi(t)$ is called the multi-scaling function. Likewise the multiwavelet function is defined from the set of wavelet function $\psi(t) = [\psi_1(t) \quad \psi_2(t) \ldots . \psi_r(t)]^T$. When r=1 $\psi(t)$ is called a scalar wavelet or simply called wavelet. Multiwavelets differ from scalar wavelet systems in requiring two or more input streams to the multiwavelet filter bank. Multiwavelets are an extension of the scalar wavelet to the vector case. As in the scalar wavelet case, the theory of multiwavelets is based on the idea of multiresolution analysis (MRA). The difference is that multiwavelets have several scaling functions. For multiwavelets, the notion of MRA is the same except that now a basis for V0 and V1 is generated by translates of N scaling functions $\Phi 1(t - k)$, $\Phi 2(t - k)$, . . . , $\Phi N(t - k)$. The multi scaling function and the multiwavelet function will satisfy matrix dilation equations (1)

$$\Phi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} H_k \Phi(2t-k)$$

$$\psi(t) = \sqrt{2} \sum_{k=-\infty}^{\infty} G_k \Phi(2t-k) \qquad (1)$$

The filter coefficients Hk and Gk are N by N matrices instead of scalar.

Corresponding to each multiwavelet system, there is a matrix-valued multi-rate filter bank [5]. A multiwavelet filter bank has "taps" that are N × N matrices. The 4-coefficient symmetric multiwavelet filter bank whose low pass filter is given by the four N × N matrices named C. Unlike a scalar 2-band Para unitary filter bank, the corresponding high pass filter specified by the four N × N matrices named D, cannot be obtained simply as an "alternating flip" of the low pass filter;

the wavelet filters D must be designed. The resulting N-channel, N × N matrix filter bank operates on N input data streams, filtering them into 2N output streams, each of which is down sampled by a factor of 2. This is shown in Fig. **1 Multi-rate Filter bank**

Each row of the multi-filter is a combination of N ordinary filters, each operating on the separate data stream.
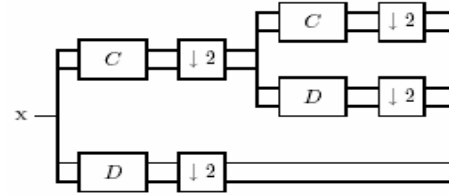

Fig. 1 Multi-rate Filter bank

III. MOTIVATION FOR MULTIWAVELETS

Algorithms based on scalar wavelets have been shown to work quite well in image and video compression. Consequently there must be some justification to use multiwavelets in place of scalar wavelets. Some reasons for potentially choosing multiwavelets are summarized below.

First, the extra degrees of freedom inherent in multiwavelets can be used to reduce restrictions on the filter properties. For example, it is well known that a scalar wavelet cannot simultaneously have both Orthogonality and symmetric property. Symmetric filters are necessary for symmetric signal extension, while Orthogonality makes the transform easier to design and implement. Also, the support length and vanishing moments are directly linked to the filter length for scalar wavelets. This means longer filter lengths are required to achieve higher order of approximation at the expense of increasing the wavelet's interval of support. A higher order of approximation is desired for better coding gain, but shorter support is generally preferred to achieve a better localized approximation of the input function. In contrast to the limitations of scalar wavelets, multiwavelets are able to possess the best of all these properties simultaneously.

Second, one desirable feature of any transform used in image compression is the amount of energy compaction achieved. A filter with good energy compaction properties can decorrelate a fairly uniform input signal into a small number of scaling coefficients containing most of the energy and a large number of sparse wavelet coefficients. This becomes important during the quantization since the wavelet coefficients are represented with significantly fewer bits on average than the scaling coefficients. Therefore better performance is obtained when the wavelet coefficients have values clustered about zero with little variance, to avoid as much quantization noise as possible Thus multiwavelets have the potential to offer better reconstructive quality at the same bit rate. Finally, multiwavelets can achieve better level of

performance than scalar wavelets with similar computational complexity.

IV. FILTER BANK APPROACH FOR MULTIWAVELETS

A. One-Dimensional Signal Processing Using Multiwavelet Filterbanks

The low pass filter C and high pass filter D in Fig. 1, consist of coefficients corresponding to the dilation equation and wavelet equation. But in the multiwavelet setting these coefficients are n by n matrices, and during the convolution step they must multiply vectors (instead of scalars). This means that multifilter banks need n input rows [11]. Separate odd and even samples.

B. Over sampled Scheme

The most obvious way to get two input rows from a given signal is to repeat the signal. Two identical rows go into the multifilter bank. This procedure, which is called as "repeated row," is shown in Fig. 2. It introduces over sampling of the data by a factor of two. over sampled representations have proven useful in feature extraction; however, they require more calculation than critically-sampled representations. Furthermore, in data compression applications, one is seeking to remove redundancy, not to increase it. In the case of one-dimensional signals the "repeated row" scheme is convenient to implement.

C. Critically Sampled scheme

A different way to get input rows for the multiwavelet filter bank is to preprocess the given scalar signal. For data compression, where one is trying to find compact transform representations for a dataset, it is imperative to find critically sampled multiwavelet transform schemes. This scheme maintains a critically sampled representation. The multifilter processes two N/2-point data streams using an approximation method suggested by Geronimo and described in [12]. This scheme in the context of Geronimo-Hardin-Massopust multiwavelets is developed; however, it works equally well for the Chui-Lian multiwavelets with minor modifications. It follows the underlying wavelet decomposition and its sampling/interpolation theory. Multiwavelet filtering of images needs two dimensional algorithms [13], [10].
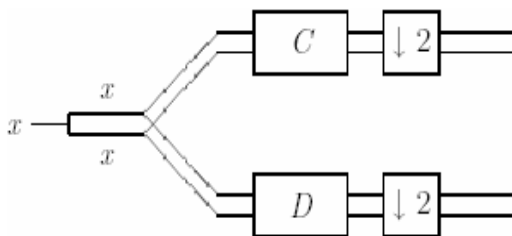

Fig. 2 Multiwavelet Filter banks with "repeated input"

One class of such algorithms is derived simply by taking tensor products of the 1-D methods described in the previous section. Another class of algorithms stems from using the matrix filters of the multiwavelet system for fundamentally 2-D processing. These alternatives are discussed now.

D. Two-Dimensional Signal Processing Using Separable scheme

Two different ways to decompose a one-dimensional signal using multiwavelets are described in section A and B. Each of these can be turned into a two-dimensional algorithm by taking a tensor product, i.e., by performing the 1-D algorithm in each dimension separately.

Suppose our 2-D data is represented as an N by N matrix. The first step is to preprocess all the rows and store the result as a square array L1 such that the first half of each row contains coefficients corresponding to the first scaling function and the second half contains coefficients corresponding to the second scaling function. The next operation is preprocessing of the columns of the array L1 to produce an output matrix L2, such that the first half of each column of L2 contains coefficients corresponding to the first scaling function and the second half of each column corresponds to the second scaling function. Then the multiwavelet cascade starts: it consists of iterative low and high pass filtering of the scaling coefficients in horizontal and vertical directions. The result after one cascade step can be realized as shown in the Figure 3. Here a typical block H2L1 contains low-pass coefficients corresponding to the first scaling function in the horizontal direction and high-pass coefficients corresponding to the second wavelet in the vertical direction. The next step of the cascade will decompose the "low-low-pass" sub-matrix L1L1, L2L1, L1L2 and L2L2 in a similar manner. As noted before, the separable product of one-dimensional "repeated row" algorithms leads to a 4:1

Data expansion, restricting the utility of this approach to applications such as denoising by thresholding, for which critical sampling is irrelevant The separable product of the approximation-based preprocessing methods described in Section C yields a critically sampled representation, potentially useful for both denoising and data compression.
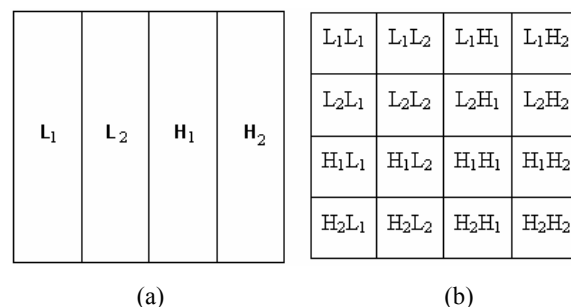
L_1	L_2	H_1	H_2

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

(a)   (b)

Fig. 3 Image subband structure for first level of decomposition.(a)Filtering along Horizontal direction.(b)Filtering along Vertical direction

E. Implementation of Multiwavelets to Image Processing

The wavelet and multiwavelet transformations are directly applicable only to one dimensional signal. But images are two dimensional signals, so we must find a way to process them with a 1-D transform. The two main categories of methods for doing this are separable and non-separable algorithms. Separable methods simply work on each dimension in series. The typical approach is to process each of the rows in order and then process each column of the result [10]. Non-separable methods, such as the factored scalar wavelet method work in both dimensions at the same time. While non-separable methods can offer benefits over separable methods, such as a savings in computation, they are generally more difficult to implement.

F. Preprocessing for Multiwavelets

Aside from decomposition concerns, there is another issue to be addressed when multiwavelets are used in the transform process. Multiwavelet filter banks require a vector-valued input signal. There are a number of ways to produce such a signal from 2D image data. Perhaps the most obvious method is to use adjacent rows and columns of the image data. However, this approach does not work well for general multiwavelets and leads to reconstruction artifacts in the low pass data after coefficient quantization. This problem can be avoided by constructing "constrained" multiwavelets, which possess certain key properties. Unfortunately, the extra constraints are somewhat restrictive; image compression test show that constrained multiwavelets do not perform as well as some other multifilter.

Another approach is to first split each row or column into two half-length signals, and then use these two half signals as the channel inputs into the multifilter. A naïve approach is to simply take the odd samples for one signal and the even samples for the second signal. This approach does not work well because it destroys the assumed characteristics of the input signal. This generally presumed that image data will be locally well-approximated by low-order polynomials, usually constant, linear, or quadratic. The high pass filters are designed to give a uniformly zero output when the input has this form. Taking alternating data points as the filter inputs alters the character of the input signal; hence the filter output will no longer be forced to zero, reducing compression performance. But there is way around this problem: one may first prefilter the two half-length signals before passing them into multifilter [12], [14].

The prefilter step adjusts the input signal properties so that one scalar signal is split in to two half-length signals in such a way that the orders of approximation built into the multifilter are utilized. The prefiltering is generally performed by taking the two signals as a 2 X N matrix (where the original 1-D signal has length 2N) and then left-multiplying by one or more 2 X 2 prefilter matrices.

G. Symmetric Signal Extension

In practice all signals have finite length, so we must devise techniques for filtering such signals at their boundaries. There are two common methods for filtering at the boundary that preserve critical sampling. The first is circular periodization (periodic wrap) of the data. This method introduces discontinuities at the boundaries; however, it can be used with almost any filter bank. The second approach is symmetric extension of the data. It has been shown that symmetric extension is the best way to handle signal boundaries. Symmetric extension preserves signal continuity, but can be implemented only with linear-phase (symmetric and/or antisymmetric) filter banks. Symmetric extension is useful for image compression applications.

H. Iteration of Decomposition

Since multiwavelets decomposition produce two low pass subbands and two high pass subbands in each dimension, the organization and statistics of multiwavelets subbands differ from the scalar wavelet case. The closer examination of the differences suggests a method for improving the performance of the multiwavelets in the image compression applications. During a single level of decomposition using a scalar wavelet transform, the 2-D image data is replaced with four blocks corresponding to the subbands representing either low pass or high pass in both dimensions. The Multiwavelets decomposition subbands are shown in Fig.4. The multiwavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of multiwavelets coefficients. Since the multiple iterations over the low pass data are desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. For example, the subband labeled L1H2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. In practice, more than one level of decomposition is performed on the image. Successive decompositions are performed on the low pass coefficients from the previous stage to further reduce the number of low pass coefficients.

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

Fig. 4 Multiwavelet decomposition subband structure for 1-level decomposition

L_1L_1	L_1L_2	L_1H_1	L_1H_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2		
H_1L_1	H_1L_2	H_1H_1	H_1H_2	L_2H_1	L_2H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2		
H_1L_1		H_1L_2		H_1H_1	H_1H_2
H_2L_1		H_2L_2		H_2H_1	H_2H_2

Fig. 5 Multiwavelet decomposition subband structure for 2-level decomposition

Since the low pass coefficients contain most of the original signal energy, this iteration process yields better energy compaction. After a certain number of iterations, the benefit gained in energy compaction becomes rather negligible compared to the extra computational effort. Usually five levels of decomposition are used in current wavelet-based compression schemes. Experiments indicate that three levels are sufficient for multiwavelets with gains in the PSNR diminishing rapidly with decomposition depth increasing above 3. A single level of decomposition with a symmetric-anti symmetric multiwavelets is roughly equivalent to two levels of wavelet decomposition. Thus a 3-level multiwavelet decomposition effectively corresponds to 6-level scalar wavelet decomposition. Since tests indicate that the improvement from depth 5 to depth 6 for scalar wavelets is negligible. A 3-level multiwavelet decomposition can be considered comparable to 5-level scalar wavelet decomposition.

Scalar wavelet transforms give a single quarter-sized low pass subband from the original larger subband. In previous multiwavelets literature a multi-level decompositions are performed in the same way. The multiwavelet decompositions iterate on the low pass coefficients from the previous decompositions, as shown in Fig. 5 In the case of scalar wavelets, the low pass quarter image is a single subband. But when the multiwavelet transform is used, the quarter image of low pass coefficients is actually a 2x2 block of subbands (the L1L1, L1L2, L2L1 and L2L2 subbands in Fig). Due to the nature of the preprocessing and symmetric extension method, data in these different subbands becomes inter mixed during iteration of the multiwavelets transform. The inter mixing of the multiwavelet low pass subbands leads to suboptimal results

V. MODIFIED SPIHT ALGORITHM FOR CODING OF MULTIWAVELET COEFFICIENTS

For evaluating the effectiveness of the Multiwavelet transform for coding images or videos at low bit rates, an effective quantization and embedded coding of coefficients [15],[16] has been realized.

An embedded coding is applied to transformed image in order to take the advantage of the decorrelation properties of its coefficients. Some of the embedded coding schemes are Embedded image coding using zero trees of Wavelet coefficients (EZW), and SPIHT.

The SPIHT coder[16] is a powerful image compression algorithm that produces an embedded bit stream from which the best reconstructed images can be obtained at various bit rates. This algorithm improves the perceptual quality of the image at all the bit rates. The Modified SPIHT algorithm for Multiwavelet differs from the ordinary SPIHT[16] algorithm by the way in which the subsets are partitioned and significant information is conveyed which is shown in Fig. 6.

A tree structure, called spatial orientation tree, defines the spatial relationship on the hierarchical pyramid. Fig. 6 shows how spatial orientation tree is defined for Multiwavelet coefficients.

The following sets of coordinates are used to present the new coding method:

O (i, j): Set of coordinates of all offspring of node (i, j)

D (i, j): set of coordinates of all descendants of node (i, j)

H (i, j): set of coordinates of all spatial orientation tree roots (nodes in the highest pyramid level)

L (i, j): $D(i, j) - O(i, j)$ (all descendents except the offspring)

A. Modified SPIHT Algorithm

All the steps of the modified SPIHT coding algorithm are same except the initialization process.

The modified SPIHT algorithm can be summarized as follows:

Initialization:

$$n = \left\lfloor \log_2(\max_{(i,j)})\{|C_{i,j}|\} \right\rfloor$$

• Set the LSP as empty list

Add the coordinates of H in which the scanning order of subbands as shown in Fig.6, to the LIP and only those with descendents also to the LIS, as type A entries in the same order. For example the order of scanning of subbands is L_1L_1, L_2L_1, L_1L_2, L_2L_2, H_1L_1, H_2L_1, H_1L_2, H_2L_2, L_1H_1, L_2H_1, L_1H_2, L_2H_2, H_1H_1, H_2H_1, H_1H_2 and H_2H_2.
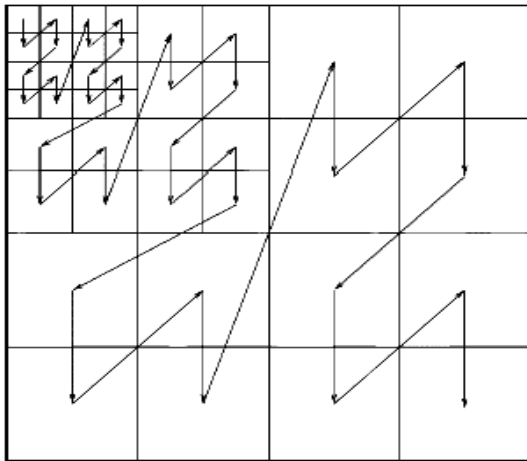
Fig. 6 Scanning and quantization order of subimages of Multiwavelet decomposition

Sorting Pass:

1)　　　　　　For each entry (i,j) in the LIP do:
1.　Output S_n (i ,j)
2.　If S_n (i ,j)=1, then move (i,j) to the LSP and output the sign of $C_{i,j}$
2)　　　　　　For each entry (i,j) in the LIS do:
3.　If the entry is of type A then
4.　Output S_n (D(i ,j))
5.　If S_n (i ,j)=1 then for each (k,l)∈O(i,j) do:
6.　Output S_n(k,l)
7.　If S_n(k,l) =1 then add (k,l) to the LSP and output the sign of $C_{k,l}$
8.　If S_n(k,l) =0 then add (k,l) to the end of LIP
9.　If $L_{i,j} \neq \phi$ then move (i, j) to the end of the LIS as entry of type B, and go to step 2) b); otherwise remove entry from the LIS.
10.　If the entry is of type B then
11.　Output S_n(L(i, j))
12.　If S_n(L(i,j))=1 then
13.　add each (k,l)∈O(i,j) to the end of the LIS as entry of type A
14.　remove (i,j) from the LIS

Refinement Pass:

For each entry (i, j) in the LSP except those included in the last sorting pass (i.e. with the same n), output the nth most significant bit of |$C_{i,j}$|.

Quantization Step Update:

Decrement the value of n by 1 and go to sorting pass if n is not less than 0.

VI. RESULTS AND DISCUSSIONS

An Fingerprint Image called Fingerprint A of Size(256 X 256) is subjected to wavelet (Haar) and Multiwavelet decomposition. The original Fingerprint Image taken for the Experimental purpose is shown the Fig. 7.The Multiwavelet filters used in this work were "GHM" pair of multifilters, Chui-Lian orthogonal multifilter "Cl", orthogonal symmetric/antisymmetric multifilter "Sa4" , Cardinal 3-balanced orthogonal multifilter "Cardbal3"and Cardinal 2-balanced orthogonal multifilter "Cardbal2" The Table-I shows the results of the Comparison of PSNR values under the

decomposition levels 2,3,4.Using HAAR wavelet. Table II to Table-VI shows the Comparison of PSNR values under decomposition levels 2,3,4 using the Multiwavelets "Cardbal3", "GHM","CL","SA4","Cardbal2" for the experimented Fingerprint A.

Fig. 7 Original Fingerprint Image (Fingerprint-A) taken

Whenever the decomposition Levels gradually increases the PSNR values are also increasing. Fig. 8 shows that an increase in the PSNR values for the increase in the decomposition levels for wavelets. Fig.9 and Fig.10 show the varying values of PSNR for multiwavelets "Cardbal3" and "cardbal2".Here the Cardinal-3 balanced Orthogonal multifilter bank and Cardinal-2 balanced Orthogonal multifilter bank performs better than

TABLE I
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF "HAAR" DECOMPOSITION

"Haar" Wavelet Decomposition				
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	14.0503	14.2049	17.3762	40.0006
0.4	14.0503	17.1153	19.8823	20.0003
0.6	14.2724	19.3412	21.4418	13.3335
0.8	14.2724	20.93	22.9169	10.0002
1	16.7379	22.5299	24.1252	8.0000

the other Multifilters because of the orthogonal Balance property which is not available in other Multifilters. Fig. 11 to Fig. 13 show that the Comparison of PSNR values for the 3 decomposition levels for wavelets and Multiwavelets.The Multiwavelets performs better than wavelets is due to the simple reason that the higher amount of energy is concentrated in the lower resolution level, which is decomposed well by the Multifilters than scalar filters.

The higher amount of scaling and wavelet function available in multifilters, provide the very good decomposition. The performance of the "Cardbal3" and "cardbal2" Multiwavelets are comparatively better than that of wavelets as the decomposition level gradually varies from 2 to 4. The increase in the PSNR value is approximately 4 to 6dB at the rates from 0.2bpp to 1bpp when levels of decomposition go higher.

TABLE II
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF
"CARDBAL3" MULTIWAVELET DECOMPOSITION

"Cardbal3" Multiwavelet Decomposition			
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	7.3867	18.4262	19.9256	40.0006
0.4	17.6141	21.8699	22.4219	20.0003
0.6	21.2487	23.7500	24.1448	13.3335
0.8	23.1553	25.0798	25.4708	10.0002
1	24.5344	26.2481	26.7384	8.0000

TABLE III
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF
"GHM" MULTIWAVELET DECOMPOSITION

"GHM" Multiwavelet Decomposition			
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	8.7547	13.2227	13.6557	40.0006
0.4	13.0103	14.3884	14.6279	20.0003
0.6	13.9619	15.6219	16.2783	13.3335
0.8	15.2830	16.9059	17.8272	10.0002
1	16.4488	19.0170	19.7649	8.0000

TABLE IV
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF
"CL" MULTIWAVELET DECOMPOSITION

"CL" Multiwavelet Decomposition			
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	3.3492	3.7769	4.2210	40.0006
0.4	3.6523	5.9839	6.7295	20.0003
0.6	5.6922	9.4599	10.0471	13.3335
0.8	9.2316	11.2157	11.7057	10.0002
1	11.0643	13.4223	14.1535	8.0000

When the decomposition levels are more than 2 there is a consistent increase in the PSNR values independent of the Rates. Irrespective of the decomposition levels the "cardbal2" performs better than "Cardbal3". Fig 14 to Fig 16 shows the rate distortion curves. It is found from these Figures that there is very good increase in the value of PSNR for any given compression ratios for Muliwavelet decomposition than that of wavelet decomposition. This shows that the user may get extra quality at the same compression ratio which is a great achievement because of the Multiresolution concept of using multiple wavelets rather than a single wavelet. The boon of Multiwavelets is especially from the multi amount of scaling function and wavelet function, where ordinary wavelet contains only one scaling and wavelet function.

TABLE V
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF
"SA4" MULTIWAVELET DECOMPOSITION

"SA4" Multiwavelet Decomposition			
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	3.3458	3.7304	4.2177	40.0006
0.4	3.5764	6.3199	7.1895	20.0003
0.6	6.0214	14.1892	14.5110	13.3335
0.8	12.6285	15.9900	16.6078	10.0002
1	15.1551	17.6224	17.9244	8.0000

TABLE VI
COMPARISON OF PSNR VALUES FOR FINGERPRINT-A UNDER 3 LEVELS OF
"CARDBAL2" MULTIWAVELET DECOMPOSITION

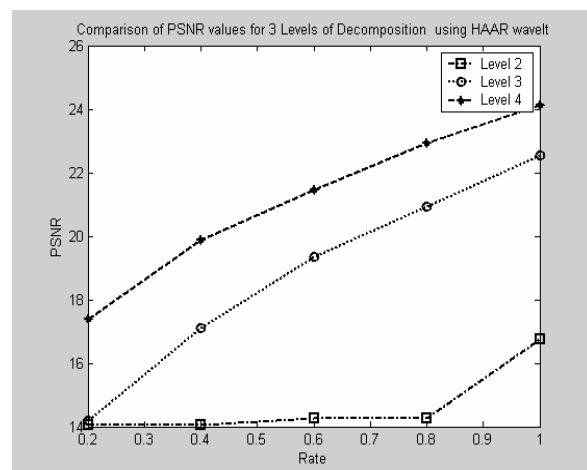| "Cardbal2" Multiwavelet Decomposition			
Rate(bpp)	PSNR(dB) Level=2	PSNR(dB) Level=3	PSNR(dB) Level=4	CR
0.2	7.4079	18.5808	20.2169	40.0006
0.4	17.7664	22.1345	22.675	20.0003
0.6	21.4868	24.0108	24.4407	13.3335
0.8	23.4823	25.3215	25.6864	10.0002
1	24.7721	26.4522	26.9804	8.0000

Fig. 8 Comparison of PSNR values for 3 levels of decomposition using "HAAR" wavelet for Fingerprint-A

Since the Fingerprint contains mostly high frequency content i.e., edges and repeated oscillatory patterns, multiwavelet decomposes the signal in a better way by using its different multifilters and provides good quality even at the lower rates. This is evident from the PSNR values available in the tables under different decomposition levels.
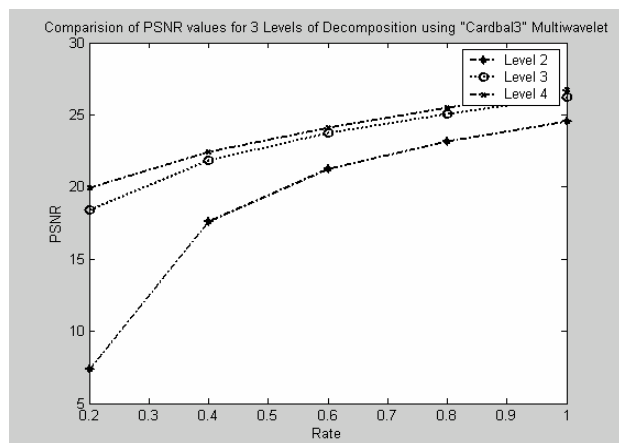
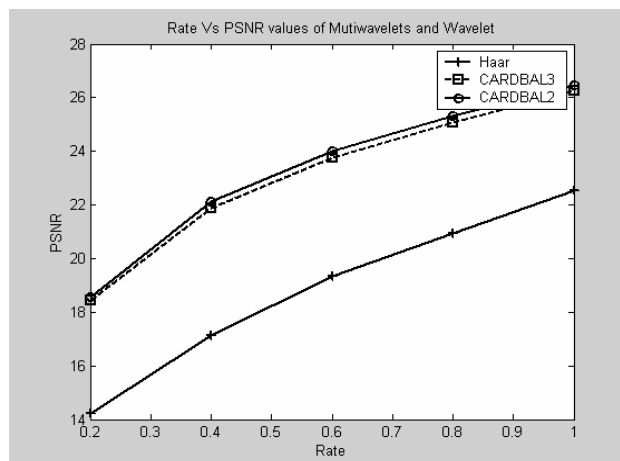Fig. 9 Comparison of PSNR values for 3 levels of decomposition using "Cardbal3"Multiwavelet for Fingerprint-A
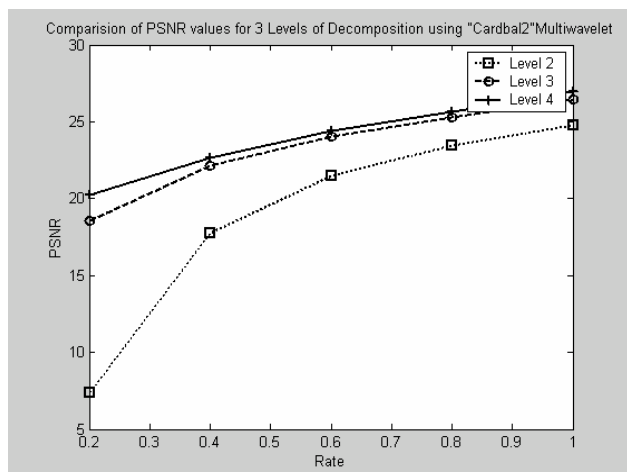

Fig. 10 Comparison of PSNR values for 3 levels of decomposition using "Cardbal2"Multiwavelet for Fingerprint-A
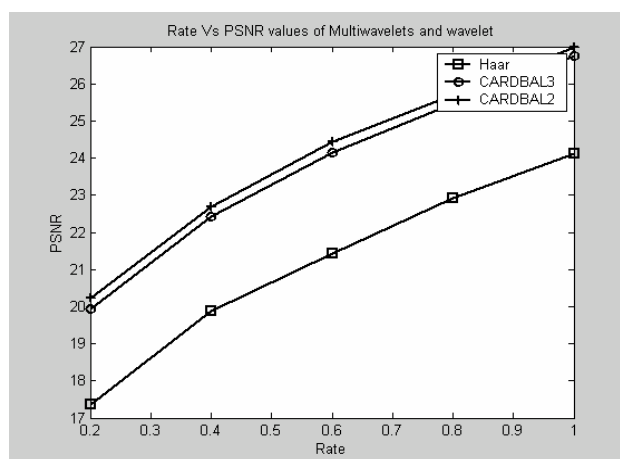

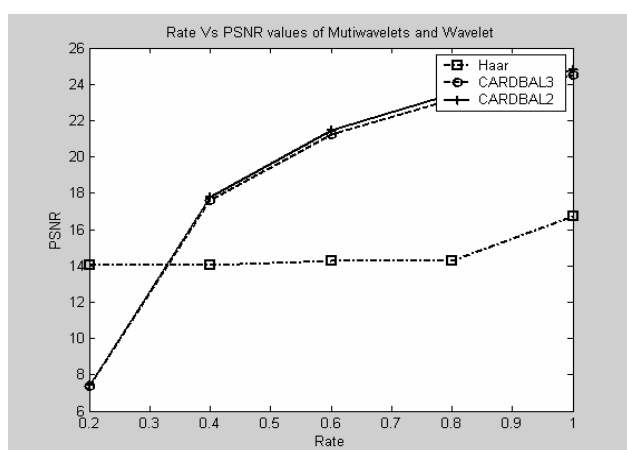Fig. 11 Comparison of PSNR values for wavelet and Multiwavelet decomposition under level=3 for Fingerprint-A

Fig. 12 Comparison of PSNR values for wavelet and Multiwavelet decomposition under level=3 for Fingerprint-A
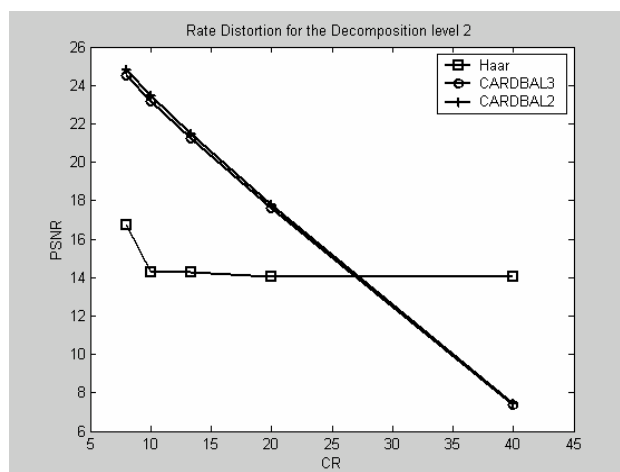

Fig. 13 Comparison of PSNR values for wavelet and Multiwavelet decomposition under level=4 for Fingerprint-A

Fig. 14 Rate distortion curves for wavelet and Multiwavelet decomposition under level=2 for Fingerprint-A
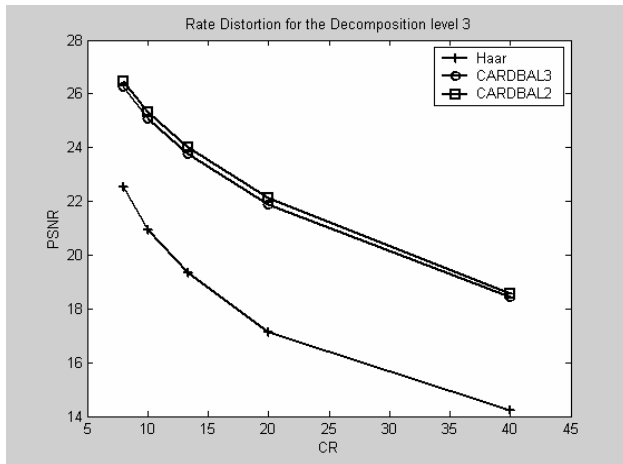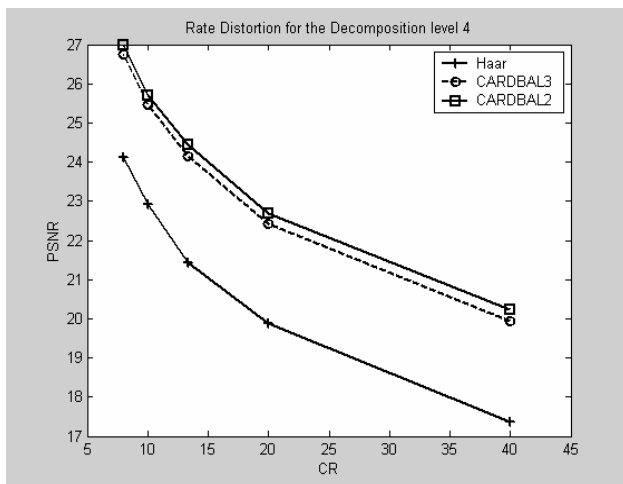
increased value in the PSNR.

Fig. 15 Rate distortion curves for wavelet and Multiwavelet
decomposition under level=3 for Fingerprint-A

Fig. 16 Rate distortion curves for wavelet and Multiwavelet
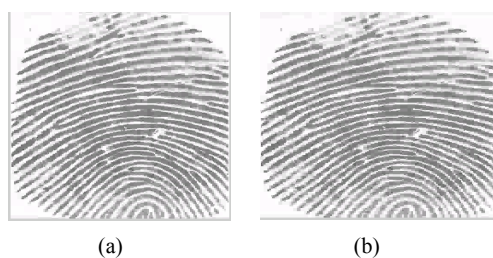decomposition under level=4 for Fingerprint-A

(a)   (b)
Fig. 17 Reconstructed Fingerprint-A. (a)using "HAAR" wavelet
with decomposition level=3 and
Rate=1bpp,PSNR=22.592dB,CR=8.(b)using "HAAR" wavelet with
decomposition level=4 and rate=1bpp,PSNR=24.12dB,CR=8

The Fig.17 shows the Reconstructed Fingerprint-A using
HAAR wavelet for the constant Rate with different levels of
decomposition. Here it shows that when the decomposition
level increases the quality increases which is shown by the

(a)   (b)
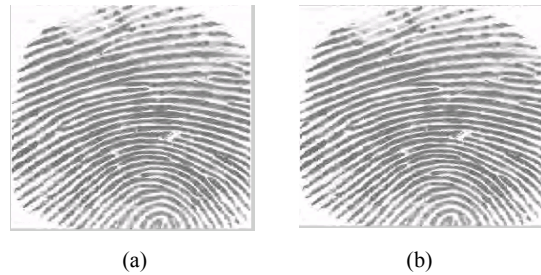Fig. 18 Reconstructed Fingerprint-A. (a)using "Cardbal3"
Multiwavelet with decomposition level=3 and
Rate=0.6bpp,PSNR=23.75dB,CR=13.33.(b)using "cardbal3"
Multiwavelet with decomposition level=4 and
Rate=0.6bpp,PSNR=24.14dB,CR=13.33

Fig 18 shows the reconstructed Fingerprint-A using
"cardbal3" Multiwavlet. Here the fig shows that we are
getting the same quality of the image as that of using wavlet
but with a lower rate that is the advantage of Multiwavelets.

VII. CONCLUSION

The performance of Multiwavelets in general depends on
the Image characteristics. For the Images with mostly low-
frequency content, (Ordinary still images) scalar wavelets
generally give better performance. However multiwavelets
appear to excel at preserving high frequency content. In
particular, multiwavelets better capture the sharp edges and
geometric patterns that occur in images. As Fingerprints are
normally high frequency patterns Multiwavelets provide better
PSNR even at the higher values Compression Ratio. Cardinal
3 balance multiwavelets and Cardinal 2 balance multiwavelets
shows very good performance since they have very balanced
orthogonal properties which are essential for signal processing
applications.

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