DTCNN Based Wavelet Decomposition Technique For Iris Image Compression Using Directional Filter Bank

Uma Rathod[1], Mandar Sohani[2], Deepali Vora[3]

[1,] Dept of Computer Engineering ,Watumull Institute of Electronic Engg. And Computer Technology ,

Mumbai University, Maharashtra, India

[2,3] Dept of Computer Science and IT, Vidyalankar Institute of Technology,

Mumbai University, Maharashtra, India

Email:ums_rathod@yahoo.co.in,

Abstract— One of the common way or method to authenticate identity of person is biometric recognition system. With the growing employment of the iris recognition systems and associated research to support this, the need for large databases of iris images is growing. Iris is considered to be the most unique attribute possessed by an individual and is regarded as the most reliable form of biometric authentication.

We propose here, a compression scheme of iris images using Mallat Based Wavelet Transform (MBWT) through Templates of Discrete Time Cellular Neural Network (DTCNN) and Directional Filter Bank (DFB) . The complex annular part of the iris portion of the eye image contains many distinctive features such as arching ligaments, furrows and ridges. The compression algorithms developed for iris images have to preserve the details present in the iris part of the image, which are used for subsequent biometric processes. The directionality features will be analyzed by means of Directional Filter banks in MBWT-DFB. The decomposed image using MBWT-DFB can be coded effectively by using SPIHT and MK-Means codebook technique. The codebook is further encoded with arithmetic encoder. We expect the better quality of the reconstructed images as compared to the 2D wavelet decomposition. Mallat algorithm is based on the multiresolution, and it represents the wavelet transform as a pyramid. Directional Filter Bank provides the flexibility to obtain good resolution, both angularly and radially. DFB has ability to extract the 2D directional information of iris image it and gives the perfect reconstruction. For encoding the SPIHT algorithm is used.

Keywords— Biometric Authentication, Compression, Iris image Compression, Multiresolution, Reconstruction, Directional Filter Bank (DFB), Mallat Based Wavelet Transform, SPIHT,DWT, Arithmetic Encoding.

INTRODUCTION

Personal identification system requires accuracy and reliability for biometric based access control system. Iris recognition system requires iris images databases for training the system. The complex annular iris part of the eye image contains the important features such as arching ligaments, furrows and collaret [1,2].

However, the increasing market saturation of biometric instead of conventional access control methods raises the need for efficient means to store such sensitive data. These motivates to effective image compression on iris biometrics to provide an efficient storage and rapid transmission of biometric records. In a modern world, biometric recognition is a common and reliable way to authenticate the identity of the person. A physiological characteristic is relatively stable physical characteristic such as fingerprints, iris pattern, retina scan etc. This kind of measurement is basically unchanging and unalterable during life time.[1]

Biometric identification or verification of identity is currently a very active field of research. Many applications that require some degree of confidence concerning the personal identification of the people involved such as banking, computer network access or physical access to secure facility are moving away from use of paper or plastic identity cards or alpha-numeric passwords. These systems are too easy to defeat. A higher degree of confidence can be achieved by using unique physical characteristics to identify a person.

The iris is a thin circular diaphragm, which lies between the cornea and the lens of the human eye. A front view of the iris is as shown in the Figure 1.

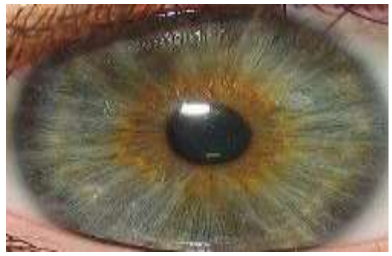

Figure1. Iris image

The function of iris is to control the amount of light entering through the pupil and this is done by the sphincter and the dilator muscles, which adjust the size of the pupil The average diameter of the iris is 12 mm and the pupil size can vary from 10% to 80% of the iris diameter.[1] Formation of iris begins during the third month of embryonic life.[2] The unique pattern on the surface of the iris is formed during the first year of life and pigmentation of stroma takes place for first few years. Formation of the unique pattern of the iris is random and not related to any genetic factors. . Due to the epigenetic nature of the iris patterns, the two eyes of an individual contain completely independent iris patterns.

A key advantage of iris recognition, besides its speed of matching and its extreme resistance to False Matches, is the stability of the iris as an internal, protected, yet externally visible organ of the eye.

NEED FOR COMPRESSION

In order to use biometrics for identification, the biometric data must be collected by some means. This may be a costly and time consuming process and the data obtained is valuable and must be protected. Furthermore, data collections can create an inordinate amount of data that puts a strain on the available storage. With the growing employment of the iris recognition systems and associated research to support this, the need for large databases of iris images is growing. If the required storage space is not adequate for these images, compression is an alternative. It allows a reduction in the space needed to store these iris images.

In this paper we are introducing a lossless compression method to compress the iris image using Mallat Based pyramidal algorithm and Directional filter bank. First Mallat based wavelet is applied on the iris image and Directional filter bank is applied on highpass band to find directionality features. This gives the better compression ratio, Mse, Psnr and the Snr.

PROPOSED SYSTEM

In this section we explain the basic idea behind the proposed scheme. The Mallat Based Wavelet Transform and Directional Filter Bank (MBWT_DFB) as shown in Figure2. has two stages ,first stage is wavelet decomposion of iris image based on Mallat pyramidal algorithm[4] for multiresolution analysis.

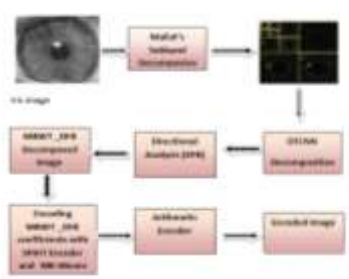

Figure 2.Block Diagram of MBWT_DFB Based Iris Image Compression.

The second stage of the MBWT_DFB is a directional filter bank (DFB)[3] analysis which provides angular decomposition. For the second stage i.e. DFB stage, we employ the iterated tree structured filter banks using fan filters. We apply DFB with the equal number of directional decompositions to each high pass band at that level of subband decomposition.

MBWT_DFB coefficient are then given as input to the encoder SPIHT and M-K Means is applied .SPIHT [7] is the well known scheme used for image compression, it partitions sets in the wavelet decomposed image using a special data structure called a spatial orientation tree. A spatial orientation tree is a group of wavelet coefficients organized into a tree rooted in the lowest frequency (coarsest scale) subband with offspring in several generations along the same spatial orientation in the higher frequency subbands. Spatial orientation tree relationship between MBWT_DFB coefficients at different scales is developed. Finally Arithmetic coding is applied for finding encoded image.

Mallat Based Wavelet Transform

Wavelet theory is vast and provides a unified support for a variety of techniques that have been developed independently for different signal processing applications. For example multiresolution signal processing was developed considering employing it in computer vision; subband coding was developed for signal and image compression; and wavelet expansion series was developed for applied mathematics. All of them have been recognized as different points of view of a unified theory. In 1988, Mallat produced a fast wavelet decomposition and reconstruction algorithm [Mal89][4]. The Mallat algorithm for discrete wavelet transform (DWT) is, in fact, a classical scheme in the signal processing community, known as a two-channel subband coder using conjugate quadrature filters or quadrature mirror filters (QMFs).

The wavelet transform can be considered, as an analysis tool able to obtain the location of a variable in the time-frequency space and it is comparable to a fixed location obtained by the short time Fourier transform.

Next, we will describe the pyramidal scheme for a wavelet representation[13].

Let D^0 be the image f, D^n is decomposed into a set of images {A_0^{n+1}, $A_1^{n+1,}$ A_2^{n+1} *and* D^{n+1}}, where each image is the result of a convolution operation between D^n and the 2D discrete filters GG,GH,HG and HH respectively. After each convolution, resultant images are subsampled, it means, we remove one column and one row for each two in order to decrease at half size; the result corresponds to a wavelet representation at resolution *n* composed by four images. The decomposition can be carried out repeatedly, preserving the A_x images and decomposing the image *D*. Resolution *n* is limited by image dimension. Figure 3 presents the scheme.

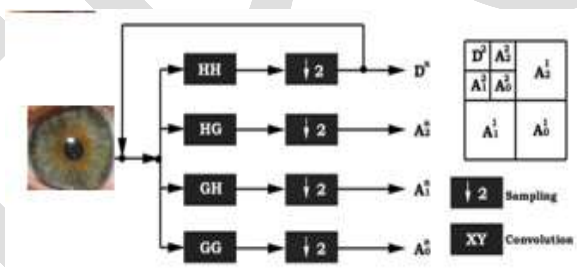

Figure3. The Pyramidal Scheme for Wavelet Representation

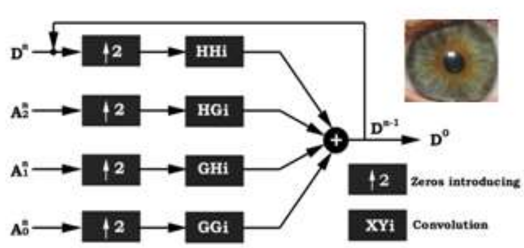

Figure4. The Wavelet Reconstruction Scheme

Reconstruction algorithm is presented in Figure 4. Initially it takes the last obtained images set { A_0^n, $A_1^{n,}$ A_2^n *and* D^n}. Every element is expanded introducing zero vectors between rows and columns. Next, a convolution operation is performed at each image with their respective reconstruction filters *GGi*, *GHi*, *HGi* and HHi. Finally, image addition is carried out in order to obtain the D^{n-1}mage. Once *D* is obtained the algorithm finishes, it corresponds to the reconstructed image.

In order to understand the multiresolution analysis concept based on Mallat's algorithm it is very useful to represent the wavelet transform as a pyramid, as shown in Figure 5. The basis of the pyramid is the original image, with C columns and R rows .

The basic algorithm for the DWT is not limited to dyadic length and is based on a simple scheme: convolution and down sampling[11] . As usual, when a convolution is performed on finite-length signals, border distortions arise. To remove these border effects, Fast Wavelet Transform was introduced. This algorithm is a method for the extension of a given finite-length signal.

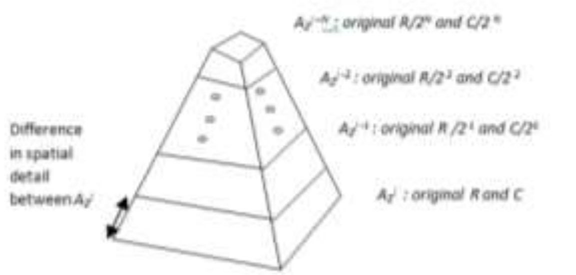

Figure5. Mallat's Pyramidal Representation

The Discrete-Time Cellular Neural Network (DTCNN)

Cellular Neural Networks (CNNs) are widely used in many applications such as forward and inverse Discrete Wavelet Transform (DWT) . It is known that CNNs offer high speed implementations. A CNN is an analog parallel computing paradigm defined in space and characterized by local connections between processing elements such as cells or neurons. In order to use CNN for any application it is necessary to design template set. The DTCNN is the dynamic clock system. The functionality of the DTCNN is completely described by a number of small matrices called the templates. Currently the design of templates is the difficult task, and it based on the geometric aspects of the problem.

The template matrix also defines the interaction between each cell and all its neighboring cells in terms of their input state and output variables. For this proposed scheme we used the r-=1 unitary neighborhood and templates are designs using the kernels [13] .The kernels for decomposition are as given

$$B_{HH}=\begin{bmatrix}0&0&0\\0&0.5&0.5\\0&0.5&0.5\end{bmatrix} B_{HG}=\begin{bmatrix}0&0&0\\0&-0.5&0.5\\0&-0.5&0.5\end{bmatrix} B_{GH}=\begin{bmatrix}0&0&0\\0&-0.5&-0.5\\0&0.5&0.5\end{bmatrix} B_{GG}=\begin{bmatrix}0&0&0\\0&0.5&-0.5\\0&-0.5&0.5\end{bmatrix}$$

are convolved with GG, GH, HG, HH subbands respectively for creating the different four templates . For reconstruction we only change the B templates, which will be

$$B_{HH}=\begin{bmatrix}0.5&0.5&0\\0.5&0.5&0\\0&0&0\end{bmatrix} B_{HG}=\begin{bmatrix}0.5&-0.5&0\\0.5&-0.5&0\\0&0&0\end{bmatrix} B_{GH}=\begin{bmatrix}0.5&0.5&0\\-0.5&-0.5&0\\0&0&0\end{bmatrix} B_{GG}=\begin{bmatrix}0.5&-0.5&0\\-0.5&0.5&0\\0&0&0\end{bmatrix}$$

The following equations define the state equation of the cell C (i, j) in discrete time.

1. State equation

$$x_{ij}= -x_{ij} + \sum_{k,l\in N(i,j)} A(i, j;k, l)\, y_{kl} + \sum_{k,l\in N(i,j)} B(i, j;k, l)\, u_{kl} + z_{i,j}$$

If acknowledgement is there wishing thanks to the people who helped in work than it must come before the conclusion and must be same as other section like introduction and other sub section.

2. The Output Equation

$$y_{ij} = f(x_{ij}) = \frac{1}{2}(x_{ij} + 1) - \frac{1}{2}(x_{ij} - 1)$$

Where x_{ij} εR, y_{kl} εR, u_{kl} εR, *and* z_{ij} εR are called state, output, input and threshold of cell C (i, j) respectively. A(i,j;k,l) and B(i,j;k,l) are called the feedback and input synaptic operators or the templates. The templates are generally designed to satisfy the requirements of the particular application. In the problem of interest, 'A' matrices (responsible for the feedback operation in CNN) are set to zero, as no feedback is involved.

Directional Filter Banks (DFB)

Bamberger and smith [10] introduced the concept of the directional filter bank. A major property 2-D directional filter bank is its ability to extract directionality features which are very much important in image analysis and other application.

The DFB is maximally decimated and obeys the perfect reconstruction, The term perfect reconstruction indicates that the total number of subband coefficients is the same as that of the original image and they can be used to reconstruct the original image without error.

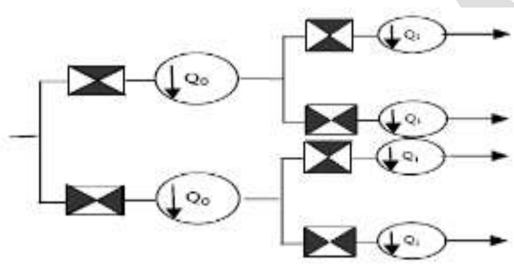

Figure6. The first two levels of the DFB. At each level, QFB's with fan filters are used. The black regions represent the ideal frequency supports of the filters

Do and Vetterli [6] proposed a new construction for the DFB to avoid modulating input image, which we can obtain the desired 2-D spectrum division as shown in Figure 6. The simplified DFB is intuitively constructed from two building blocks. The first is a two-D spectrum into two directions: horizontal and vertical. The second is a shearing operator, which used to reordering the image samples. We used the DFB which constructed by first method.

The general construct of the DFB[12] involves a tree structure of 2-band splits, where each split increases the angular resolution by a factor of 2.

A typical, uniform angular decomposition may be represented by a balanced tree of 2-band splits, and is presented in· Figure 7. Conversely, applications that require higher angular frequency resolution only in particular directional bands may use an unbalanced tree.

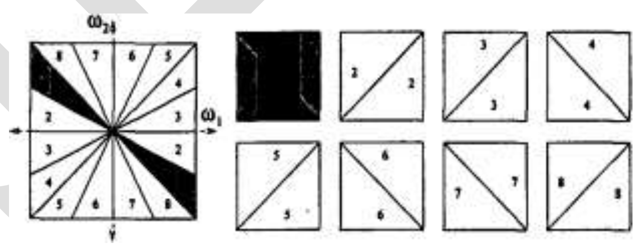

Figure7. A depiction of the passbands associated with an 8-band DFB, showing how directional bands from the input (left) map to their corresponding subbands (right).

It is possible to generate 2-D passband regions along radial frequency lines in addition to angular partitions using this new family of filter banks. Most of the information necessary to derive the octave-band DFB lies in the derivation of the conventional DFB.The successive application of DFB splits within DFB sub-bands leads to a large family of octave-band decompositions, where each member can be defined unambiguously by the number of angular bands and the number of octave bands.

Image Codec (SPIHT*)* And MK-Means

SPIHT[10] is sophisticated encoding for next generation .Wavelet wavelet transform following bit plane sequence ,encoding exploiting the properties of wavelet transformed images to increase its efficiency. SPIHT[8] codes the individual bits of image wavelet transform following bit plane sequence, SPIHT[9] is capable of recovering the image perfectly by coding all bits of transform.

Modified K-Means is based on K-Means clustering (MacQueen, 1967)[14] is a method commonly used to automatically partition a data set into k groups. It proceeds by selecting k initial cluster centers set to 6 and then iteratively refining them code vector clusters till k value 6 is satisfies. The modifications in existing original idea in K-Means clustering is to set the number of clusters k value to 6 and consider first k objects from data set D as clusters & their 6 representative centroids.

EXPERIMENTAL RESULTS

The proposed compression method based on MBWT-DFB with the SPIHT Encoder scheme is tested on iris images having a size of 128x128 pixels with 8 bit pixel brightness. The images used in this research has iris database of Palacky University iris database[17] which composed of images of 16 different person eyes (left, right), with 3 images of each eye i.e each persons 6 images (totaling 96 iris images).

Different samples are taken from the database and various parameters are obtained like SNR, PSNR, MSE CR, and BPP. Results obtained are as in Table 1.

Table 1. MSE, SNR, PSNR ,CR ,BPP values of MBWT_DFB compression Technique

Image Name	Memory size In bits	After compression Memory size	SNR	PSNR	MSE	CR	BPP of original image	BPP of Compress image
1L-1.bmp	139696	62368	16.2321	42.2448	3.8779	55.3545	8.5264	3.8066
1L-2.bmp	139696	62952	16.4031	41.9848	4.1172	54.9364	8.5264	3.8423
1L-3.bmp	139696	63128	16.3966	41.9889	4.1133	54.8104	8.5264	3.853
1R-1.bmp	139696	62296	16.4481	41.9011	4.1973	55.406	8.5264	3.8022
1R-2.bmp	139696	61824	16.5807	41.8111	4.2852	55.7439	8.5264	3.7734
1R-3.bmp	139696	62064	16.333	42.0628	4.0439	55.5721	8.5264	3.7881
7L-1.bmp	139696	61080	16.3655	41.293	4.8281	56.2765	8.5264	3.728
7L-2.bmp	139696	60920	16.3331	41.2764	4.8467	56.391	8.5264	3.7183
7L-3.bmp	139696	60888	16.3215	41.3469	4.7686	56.4139	8.5264	3.7163
7R-1.bmp	139696	60912	16.3078	41.3594	4.7549	56.3967	8.5264	3.7178
7R-2.bmp	139696	61240	16.3198	41.3265	4.791	56.162	8.5264	3.7378
7R-3.bmp	139696	61384	16.2725	41.3818	4.7305	56.0589	8.5264	3.7466
16L-1.bmp	139696	22728	16.6607	40.2945	6.0762	83.7304	8.5264	1.3872
16L-2.bmp	139696	22648	16.637	40.3642	5.9795	83.7877	8.5264	1.3823
16L-3.bmp	139696	22800	16.5731	40.477	5.8262	83.67	8.5264	1.39
16R-1.bmp	139696	22464	16.5525	40.4653	5.8418	83.9194	8.5264	1.3711
16R-2.bmp	139696	22040	16.5064	40.4741	5.8301	84.2229	8.5264	1.3452
16R-3.bmp	139696	21016	16.5235	40.5304	5.7549	84.95	8.5264	1.28

The iris images(16.bmp) having more frequent features giving higher MSE and compatible PSNR, Where as iris images(1.bmp) having less features and more frequent texture information giving less MSE and higher PSNR When we are comparing 1.bmp and 16.bmp images results it is observed that CR of 16.bmp images is higher than that of 1.bmp images because of 16.bmp images iris region has frequent features and high intensity pixels are more in size. So a DFB band finds these frequent regions and gives better Compression Ratio.

CONCLUSION

In this paper, a Mallat based wavelet and DFB is used to compress iris images is proposed. Instead of using basic wavelets transforms alone it combined with DFB are used. Mallat Based wavelet and DFB are together used for spars representation and for encoding SPIHT and MK-Means is used as described in above section. Mallat Based Wavelet Transform is used for multiresolution analysis and templates are design in DTCNN domain, for directionality features Directional Filter bank are used. A major property 2-D directional filter bank is its ability to extract directionality features which are very much important in image analysis and other application. The DFB is maximally decimated and obeys the perfect reconstruction, The term perfect reconstruction indicates that the total number of subband coefficients is the same as that of the original image and they can be used to reconstruct the original image without error. Experimental results show that it gives good CR, SNR, PSNR, and MSE values

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