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MULTIMODAL WAVELET TRANSFORMS FOR FACE RECOGNITION

Muvva china krishnaiah*1 and M.Pradeep[2]

*[1]PG Student, ECE Department, Indira Institute of Technology, Markapur

[2]Assistant Professor, ECE Department, Indira Institute of Technology, Markapur

ABSTRACT

In this brief, multimodal wavelet transforms for face recognition is proposed for feature extraction for improve the efficiency for the face recognition. Face recognition system is widely used for detect the given input image from the different database. Face recognition scheme applications are military, medical, entertainment and security purpose. So far number of feature extraction techniques has been researched on different wavelets. In this paper to enhance image retrieval recognition efficiency detect the edge contours of the given input data. Face recognition algorithms concentrate on the different distance measure techniques. In this multimodal analysis introduced the different combinations of discrete wavelets such as discrete wavelet transform (DWT) and contourlet transform. The experimental results of the proposed paper uses YALE and ORL database. As compared to existing techniques this proposed method gives better results in terms of recognition efficiency and computaltional rates.

***Keywords**: KLDA, local mean nearest neighbor and distance measures classifiers.*

I. INTRODUCTION

In recent days, face recognition system has gained its popularity due to its importance in security and surveillance. This system is useful in computer vision and biometric authentication. Breaks down a signal into constituent sinusoids of different frequencies. Here wavelet is also called as small wave. Different wavelet can be represented as convert a signal into a series of wavelets, provide a way for analyzing waveforms, bounded in both frequency and duration, allow signals to be stored more efficiently than by Fourier transform, be able to better approximate real-world signals, well-suited for approximating data with sharp discontinuities. Notice gross features with a large "window"Notice small features with a small. The history of the wavelet transforms shows with different examples. Pre-1930.Joseph Fourier (1807) with his theories of frequency analysis. The 1930s using scale-varying basis functions; computing the energy of a function, 1960-1980 Guido Weiss and Ronald R. Coifman; Grossman and Morlet. post-1980 stephane Mallat; Y. Meyer; Ingrid Daubechies; wavelet can also represented as like this Furthermore, it's known that these filters allow perfect reconstruction of a time-series by

Summing its low-pass and high-pass versions. Basis functions of the wavelet transform (WT) are small waves located in different times, they are obtained using scaling and translation of a scaling function and wavelet function therefore, the WT is localized in both time and frequency In nonlinear approximation we keep only a few significant coefficients of a signal and set the rest to zero. Then we reconstruct the signal using the significant coefficients. WT produces a few significant coefficients for the signals with discontinuities. Thus, we obtain better results for WT nonlinear approximation when compared with the FT. This means that a time compression of the wavelet by a factor of 2 will stretch the frequency spectrum of the wavelet by a factor of 2 and also shift all frequency components up by a factor of 2. The questions are of discrete wavelet transform are Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. What if we choose only a subset of scales and positions at which to make our calculations? It turns out, rather remarkably, that if we choose scales and positions based on powers of two -- so-called dyadic scales and positions -- then our analysis will be much more efficient and just as accurate. We obtain just such an analysis from the discrete wavelet transform (DWT). The approximations are the high-scale, low-frequency components of the signal. It is important to note that in the above transforms the wavelet basis functions are not specified. This is a difference between the wavelet transform and the Fourier transform, or other transforms. From Fourier theory we know that compression in time is equivalent to stretching the spectrum and shifting it upwards. Then to obtain just such an analysis from the discrete wavelet transform (DWT). The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

Basics concepts of different waveare discussed in section II. Proposed method is discussed in section III. Experimental results are presented in section IV. Concluding remarks are discussed in section V.

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II. MULTIMODAL WAVELET TRANSFORMS

In general, a family of representations using:hierarchical (nested) basis functions,finite ("compact") support,basis functions often orthogonal,fast transforms, often linear-time, For easier calculation we can to discrete continuous signal.We have a grid of discrete values that called dyadic grid .Important that wavelet functions compact (e.g. no overcalculatings). A two dimensional (image) compression, using 2D wavelets analysis. The image is a Fingerprint. FBI uses a wavelet technique to compress its fingerprints database. The wavelet transform is a tool for carving up functions, operators, or data into components of different frequency, allowing one to study each component separately.

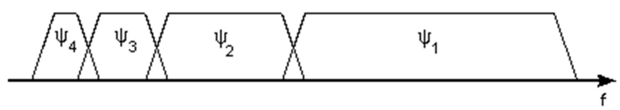
The factor of two scaling means that the spectra of the wavelets divide up the frequency scale into *octaves* (frequency doubling intervals) As we showed previously, the coefficients of Y_1 is just the band-passes filtered time-series, where Y_1 is the wavelet, now viewed as a bandpass filter.

It turns out that its easy to pick the low-pass filter, $f^{lp}(w)$. It must match wavelet filter, Y(w). A reasonable requirement is:

$$|f^{lp}(w)|^2 + |Y(w)|^2 = 1$$

That is, the spectra of the two filters add up to unity. A pair of such filters are called *Quadature Mirror Filters*. They are known to have filter coefficients that satisfy the relationship:

$$Y_{N-1-k} = (-1)^k f^{lp}_k$$



Concentrated on the global information of the face images. Only the pixel information is considered and the relation with the neighboring pixels is missed. In order to incorporate the relations with the neighboring pixels they introduced the local matching methods. In this local matching method, it considers only local information but it misses the global information of the face images. Most natural signals are smooth with a few discontinuities (are *piece-wise smooth*) speech and natural images are such signals Hence, WT has better capability for representing these signal when compared with the FT Good nonlinear approximation results in efficiency in several applications such as compression and denoising Series Expansion of Discrete-Time Signals, Suppose that is a square-summable sequence, that is orthonormal expansion of is of the form where is the transform of the basis functions satisfy the orthonormality constraint The basic idea of the wavelet transform is to represent any arbitrary function *f(t)* as a superposition of a set of such wavelets or basis functions, These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts).

Similarly, the Continuous Wavelet Transform (CWT) is defined as the sum over all time of the signal multiplied by scale , shifted version of the wavelet function,

$$\gamma(s,\tau) = \int f(t)\Psi^*_{s,\tau}(t)dt$$

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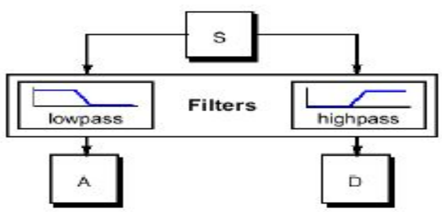
where * denotes complex conjugation. This equation shows how a function f(t) is decomposed into a set of basis function, called the *wavelets*. Z=r+iy, z*=r-iy. The variables s and t are the new dimensions, *scale* and *translation (position)*, after the wavelet transform. The wavelets are generated from a single basic wavelet , the so-called *mother wavelet*, by scaling and translation:

$$\Psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right)$$

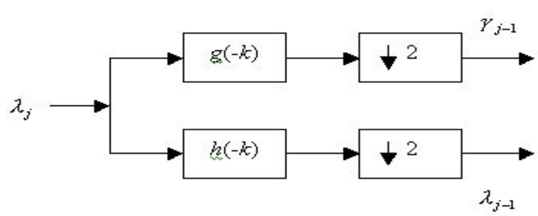
s is the scale factor, t is the translation factor and the factor $s^{-1/2}$ is for energy normalization across the different scales.

$$F\{f(at)\} = \frac{1}{|a|}F\left(\frac{\omega}{a}\right)$$

This means that a time compression of the wavelet by a factor of 2 will stretch the frequency spectrum of the wavelet by a factor of 2 and also shift all frequency components up by a factor of 2. The questions are of discrete wavelet transform are Calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. What if we choose only a subset of scales and positions at which to make our calculations? It turns out, rather remarkably, that if we choose scales and positions based on powers of two -- so-called dyadic scales and positions -- then our analysis will be much more efficient and just as accurate. The filtering process, at its most basic level, looks like this:



The original signal, S, passes through two complementary filters · Unfortunately, if we actually perform this operation on a real digital signal, we wind up with twice as much data as we started with. Suppose, for instance, that the original signal S consists of 1000 samples of data. Then the approximation and the detail will each have 1000 samples, for a total of 2000. To correct this problem, we introduce the notion of *downsampli*ng. This simply means throwing away every second data point. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components. This is called the *wavelet decomposition* A more sophisticated wavelet – uses slightly more complex P and U operators, Uses *linear prediction* to determine odd samples from even samples



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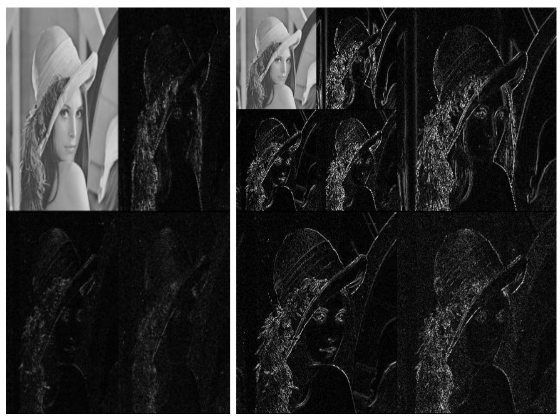
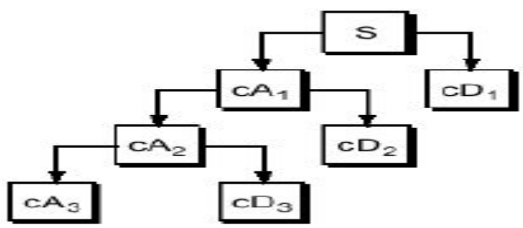
(a) Original *(b) One-level haar*



(c) One level linear spline (d) two-level haar



III. PROPOSED SYSTEM

Proposed Algorithm

Proposed method is presented below:

1. The input database images can be represented as in square matrix interms of M*N. There are N face images belonging to M persons in the training set; N = N1+N2+N3+…NM. Images size is represented as no. of rows and columns (A1×A2).
2. Apply DWT transform for calculating different coefficients in terms of LL, LH, HL, and HH band.
3. Consider LL band for extraction very high content of the input images to enhance the feature extraction.
4. Similarly same procedure for independent component analysis and linear discriminate analysis.
5. Each of them can be expressed in the form of d-by-L Eigenvector matrix.
6. Afterwards, S extracted local sub feature weights of an individual vertically are synthesized into a global feature.

7. At final stage necessary to identify a new test image, this image also partitioned into S sub-pattern images. Each of them is represented as C test i and it's vertically centered.
8. Finally, the identification of the test image is done by using nearest neighbor classifier with cosine measure, in which the cosine of the angle between the test image and each training image in the database.

IV. EXPERIMENTAL RESULTS

Recognition performance in terms of average recognition rate and recognition time of the proposed face recognition system is tested by conducting an experiment on hybrid approach face database. A face database [6] test set was constructed by selecting 100 images of 10 individuals, ten images per person. These images of a person used for training and testing. the experimental results are tabulated in Table 1. Since the recognition accuracy of the sub-pattern

image, several sizes of sub-pattern images were used in our experiments as shown below: 56×46(S=4), 28×23(S=16), 14×23(S=32), 7×23(S=64), and 4×23(S=112). Result has been presented in hybrid approach with S<64.

A. Feature selection

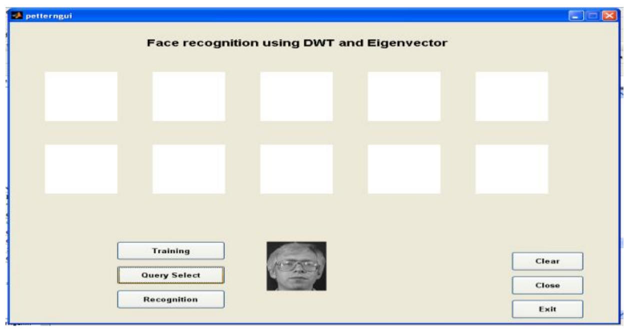


Figure2: Sample image

A sample image from face database and by using sub-pattern technique it can be divided by equal parts. Feature of the query image size is (64×1) by using sub-pattern method. Some of the recognized results when all the 10 images (N=10) in one subject of the image database are recognized are shown in figure 3. From the query image feature is taken based on sub-pattern method .After that in this paper we take only 64 feature of this query image. That may be depends up on the sub-parts of this image(S=16). For each sub-pattern we consider four positive eigenvectors that is largest eigenvector of the subpart. It is represented as only local feature of the query image. After that combination of all sub-parts local feature it can be represented as global feature of the query image. Comparative performance of all training global feature with this query image finally recognized results images with top left image as query image. Subpattern method and principal component analysis [8] can significantly improve the recognition accuracy of sub pattern vertically centered method. Since the vertical centering process centers the data by removing the mean of each image, it can be used to eliminate the effect of the values. In other words, the property of vertical centering process [9] can be helpful in eliminating the shifted values of original-pixels. Further, the sub-pattern technique can be utilized to encourage the efficiency of the vertical centering process. Therefore, sub-pattern technique is actually useful to vertical centering process of sub-pattern technique. The vertical centering may benefits for the recognition in varying illumination. Now, we have confirmed this possible forecast and strongly increased the efficiency of the vertical centering process by sub-pattern technique in this paper. From the total experimental results, it can also be seen that for expression variant test, sub-pattern technique and Eigen vector can slightly improve weighted angle based approach classifier, the similarity between a test image and training image is defined as In the weighted angle based approach method cosine measurement.

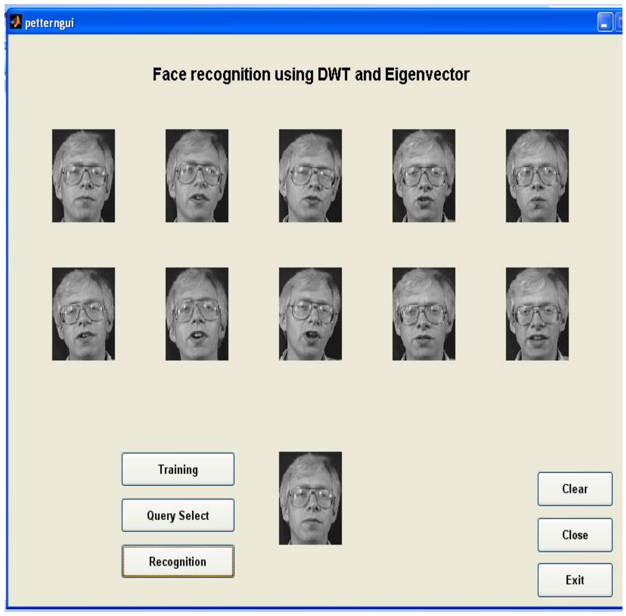


Figure 3. Recognized images.

B. Average recognized rate

The average recognized rate for the query is measured by
counting the number of images from the same category which are found in the top 'N' matches.

Table 1. Recognized rate on face database.

Methods	Number of top matches				
	1	3	5	7	10
DCT	100	58.5	50.5	44.2	36.25
DWT	100	61.5	59	58	49.5
Multimodal wavelet transforms	100	78	74	70	65.5

(1, 3, 5,7,10 are Top 'N' recognized images)

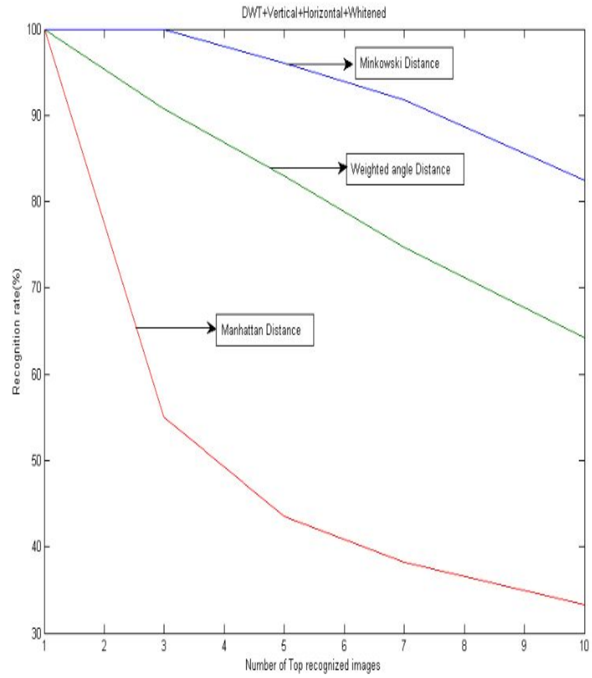


Figure 4. Comparative recognition rates.

C. Recognized Time

Face recognition system with weighted angle based approach technique for largest four eigenvector recognized time is 50.42 seconds (training time is 50 seconds and recognitized time is 0.42 seconds), hybrid approach technique for all positive eigenvector recognized time is 51.20 seconds, Existing method in DCT recognized time is 1.65 seconds, DWT time is 2.90 seconds and Multimodal wavelets method recognized time is 2.72 seconds.

V. CONCLUSION

Facial multimodal wavelets for face recognition have been implemented in this paper. Face recognition expressions recognition based on dimensionality reduction technique. Global feature vector is generated and used for face recognition. Horizontal and vertical variations are considered in feature vector. Facial expression recognition based on dimensionality reduction techniques gives better performance in terms of average recognized rate and retrieval time compared to existing methods.

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