

Comparative Study of Multiresolution Analysis and Distance Measures for Face Recognition

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Abstract—In this paper we have compared 7 distance measures for face recognition using multi resolution analysis. Different wavelet families like Haar, Daubechies, Symlet, Biothogonal are used to test the results. Recognition experiments are performed using the database containing images of 400 persons. The experiments showed that the best recognition results are achieved using Manhattam distance measure on A2 and A3 subbands of symlets 8 wavelet.

Index Terms—distance measure, face recognition, wavelet

I. INTRODUCTION

Multiresolution methods provide powerful signal analysis tools, which are widely used in feature extraction, image compression and denoising applications. Wavelet decomposition is the most widely used multiresolution technique in image processing. The advantages of wavelet are good time and frequency localizations [1], [2]. Decomposing an image using wavelet reduces the resolutions of subband images hence computational complexity will be reduced drastically by working on lower resolution image. Two dimensional wavelet transform is performed by consecutively applying one-dimensional wavelet transform to the rows and columns of the two dimensional data.

In this paper images are divided into two groups as test images and train images. Different families of wavelet are used for decomposition of images. Images are decomposed up to four levels and low frequency subband at each level is used for face recognition. Comparison between test image and train images is performed by calculating the distance between subbands of these images. Usually comparison of face images is performed by calculating the Euclidean distance. Sometimes the angle based distance is also used. Although there exist many other distance measures [3], [4]. In this paper we compare recognition performance of 7 distance measures including Euclidean and angle-based. The experiments showed that Manhattam distance measure gives the best results.

II. WAVELET DECOMPOSITION

A face recognition system, in general, consists of two major modules, a feature extraction and a classification stage. The accuracy of the system depends strongly on features extracted to represent the face images and classification methods used to discriminate among faces. The purpose of feature extraction is to provide useful information which efficiently represents the face images without redundancy. Meanwhile it can greatly reduce the dimensionality of the original image representation.

The wavelets are a set of functions that result from a shift and dilation of the original waveform. Compared to the traditional Fourier transform, all wavelet transforms are forms of time-frequency joint representation with coefficients in linear combination of the wavelet functions. A family of wavelets can be obtained by scaling ψ by s and translating it by u .

$$\psi_{u,s}(t) = s^{-1/2} \psi\left(\frac{t-u}{s}\right) \quad (1)$$

The DWT of a 1-D signal $f[n]$ with period N is computed as:

$$Df[n, a^j] = \sum_{m=0}^{N-1} f[m] a^{-j/2} \psi\left(\frac{m-n}{a^j}\right) \quad (2)$$

where m and n are integers. The value of a is equal to 2 for a dyadic transform. The information corresponding to the scales larger than a^j is also required, which is computed by a scaling filter and is given by

$$SFf[n, a^j] = \sum_{m=0}^{N-1} f[m] a^{-j/2} \phi\left(\frac{m-n}{a^j}\right) \quad (3)$$

where $\phi(n)$ is the discrete scaling (low-pass) filter.

For the 2-D data, the implementation is carried out by applying a 1-D transform to all the rows of the input image data, and then repeating on all of the columns. The 2-D transform uses a family of wavelet functions and its associated scaling function to decompose the original image into different subbands, namely the low-low (LL), low-high (LH), high-low (HL) and high-high (HH) subbands, which are also known as A, V, H, D respectively.

Each of the channels of the wavelet decomposition can be further decomposed using the discrete wavelet transform, thus a multi-level representation of the face is obtained.

In this paper ORL database is used to perform the experiments. Fig. 1 shows one of the images from database and the four level decomposition of image.

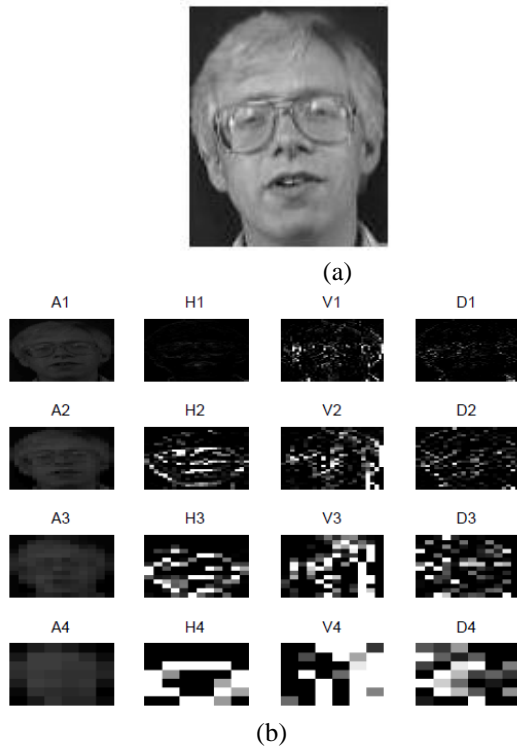


Figure 1. (a) Original image from ORL database

(b) 4-level decomposition of original image

III. FAMILIES OF WAVELET TRANSFORM FOLLOWING WAVELET FAMILIES ARE USED FOR EXPERIMENTS.

A. Haar Wavelet:

In mathematics, the Haar wavelet is a certain sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. The Haar wavelet's mother wavelet function $\psi(t)$ is as shown in Fig. 2.

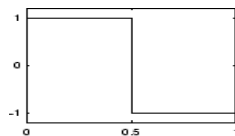


Figure 2. Wavelet function ψ for Haar wavelet

B. Daubechies Wavelet

Named after Ingrid Daubechies, the Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function which generates an orthogonal

multiresolution analysis. The names of the Daubechies family wavelets are written dbN, where N is the order of the wavelet. The db1 wavelet is the same as Haar wavelet. The wavelet functions ψ of the next nine members of the family are shown in Fig. 3.

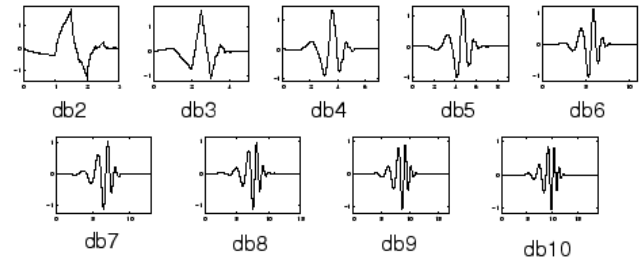


Figure 3. Wavelet functions ψ for the nine members of Daubechies family

C. Biorthogonal Wavelet

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions. In the biorthogonal case, there are two scaling functions Φ, Φ' , which may generate different multiresolution analyses, and accordingly two different wavelet functions Ψ, Ψ' . The wavelet functions Ψ and Ψ' for boir6.8 family of biorthogonal wavelet is shown in Fig. 4.

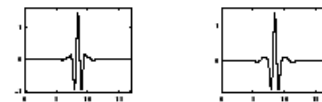


Figure 4. The wavelet functions Ψ and Ψ' for boir6.8 family of biorthogonal wavelet

D. Symlets Wavelet

The symlets are nearly symmetrical wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. The wavelet functions ψ for the Symlets wavelet family are shown in Fig. 5.

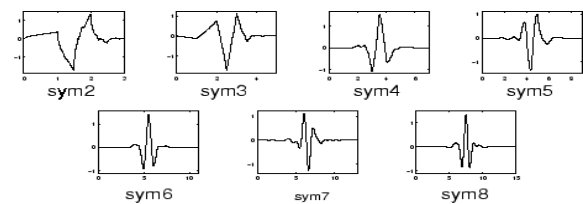


Figure 5. Wavelet functions ψ for the Symlets wavelet family

IV. DISTANCE MEASURES

Let X, Y is the feature vectors of length n . Then we can calculate the following distances between these feature vectors [5], [6], [7]:

- Manhattan distance (L1 metrics, city block distance)

$$d(X, Y) = L_{p=1}(X, Y) = \sum_{i=1}^n |x_i - y_i| \quad (4)$$

- Euclidean distance (L2 metrics)

$$d(X, Y) = L_{p=2}(X, Y) = \|X - Y\| \quad (5)$$

- Minkowski distance (L_p metrics)

$$d(X, Y) = L_p(X, Y) = \left(\sum_{i=1}^n \|x_i - y_i\|^p \right)^{1/p} \quad (6)$$

- Squared Euclidean distance(sum square error, SSE)

$$d(X, Y) = L_{p=2}^2(X, Y) = SSE = \|X - Y\|^2 \quad (7)$$

- Mean squared error (MSE)

$$d(X, Y) = \frac{1}{n} L_{p=2}^2(X, Y) = MSE = \frac{1}{n} \|X - Y\|^2 \quad (8)$$

- Angle –based distance

$$d(X, Y) = -\cos(X, Y) = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2} \quad (9)$$

- Chi square distance

$$d(X, Y) = x^2 = \sum_{i=1}^n \frac{(x_i - y_i)^2}{x_i + y_i} \quad (10)$$

These all distance measures are compared for face recognition using 4 LL subbands of different wavelet transforms.

V. EXPERIMENTS AND RESULTS

The experiment is performed using face database from AT&T (Olivetti) Research Laboratories, Cambridge (ORL database) [8]. The database contains 40 individuals with each person having ten frontal images. There are variations in facial expressions such as open or closed eyes, smiling or no smiling, and glasses or no glasses. All images are 8-bit grayscale of resolution 112 X 92 pixels. We selected 340 images (6 images per person) for training and remaining 160 images for testing.

We extracted image features using different wavelet transforms such as Haar, Daubechies, Coiflet, Symlet, Biothogonal. Four level decomposition is carried out on images and LL subband of each level is used for distance measure. Resolution of first level LL subband (A1) i image is 56 X 46, second level LL subband (A2) is 40 X 35, third level LL subband (A3) is 28 X 26 and of fourth level LL subband (A4) is 22 X 21.

The results of experiments are summarized in Tables I – VI and graphs are shown in Fig. 6. In these tables and graphs we can see how different wavelets and distance measures affect the recognition rate.

TABLE I. RECOGNITION RATE (%) USING DB1 FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhattan	Euclidean	Minkowski	SSE	MSE	Angle based	Chi -Square
A1	97.500	90.625	88.125	94.375	94.3750	92.50	93.750
A2	97.500	90.625	90.625	95	95	93.75	95.625
A3	97.500	92.500	93.125	96.250	96.2500	96.25	96.875
A4	96.875	93.125	95.625	97.500	97.5000	96.875	96.250

TABLE II. RECOGNITION RATE (%) USING DB2 FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhattan	Euclidean	Minkowski	SSE	MSE	Angle based	Chi -Square
A1	97.500	91.250	86.250	94.375	94.375	93.125	93.75
A2	98.125	92.500	93.125	96.250	96.250	94.375	96.25
A3	98.125	93.750	93.125	96.250	96.250	96.250	96.25
A4	97.500	94.375	90	95.625	95.625	95	96.25

TABLE III. RECOGNITION RATE (%) USING DB3 FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhattan	Euclidean	Minkowski	SSE	MSE	Angle based	Chi -Square
A1	97.500	91.875	87.500	94.375	95.625	92.500	94.375
A2	97.500	91.250	91.250	95.625	95	93.750	95.625
A3	97.500	93.125	93.750	95.625	95	94.375	96.875
A4	98.125	95	93.125	95.625	95.625	95.625	96.250

TABLE IV. RECOGNITION RATE (%) USING BIOR6.8 FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhattan	Euclidean	Minkowski	SSE	MSE	Angle based	Chi -Square
A1	97.5000	91.250	86.250	95	95	91.875	95
A2	96.8750	91.875	90	95	95	94.375	95.625
A3	96.8750	93.125	91.875	95	95	95.625	96.250
A4	98.1250	92.500	92.500	95	95	95.625	96.875

TABLE V. RECOGNITION RATE (%) USING BIOR6.8 FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhattan	Euclidean	Minkowski	SSE	MSE	Angle based	Chi -Square
A1	97.500	93.750	88.750	95	95	92.500	96.875
A2	99.375	93.125	89.375	96.25	96.25	95	98.125
A3	98.125	95	91.250	97.50	97.50	96.250	97.500
A4	97.500	92.500	95	96.25	96.25	95.625	96.250

TABLE VI. RECOGNITION RATE (%) USING SYMLETS (SYM8) FOR DIFFERENT DISTANCE MEASURES ON LL SUBBANDS A1, A2, A3, A4

	Manhat	Euclidean	Minkow	SSE	MSE	Angle based	Chi -Square
A1	97.50	93.125	87.50	96.250	96.250	93.125	96.250
A2	99.37	95.625	90	97.500	97.500	95.625	98.750
A3	99.37	95.625	93.75	96.875	96.875	96.250	98.125
A4	96.25	91.875	92.50	96.250	96.250	96.250	96.875

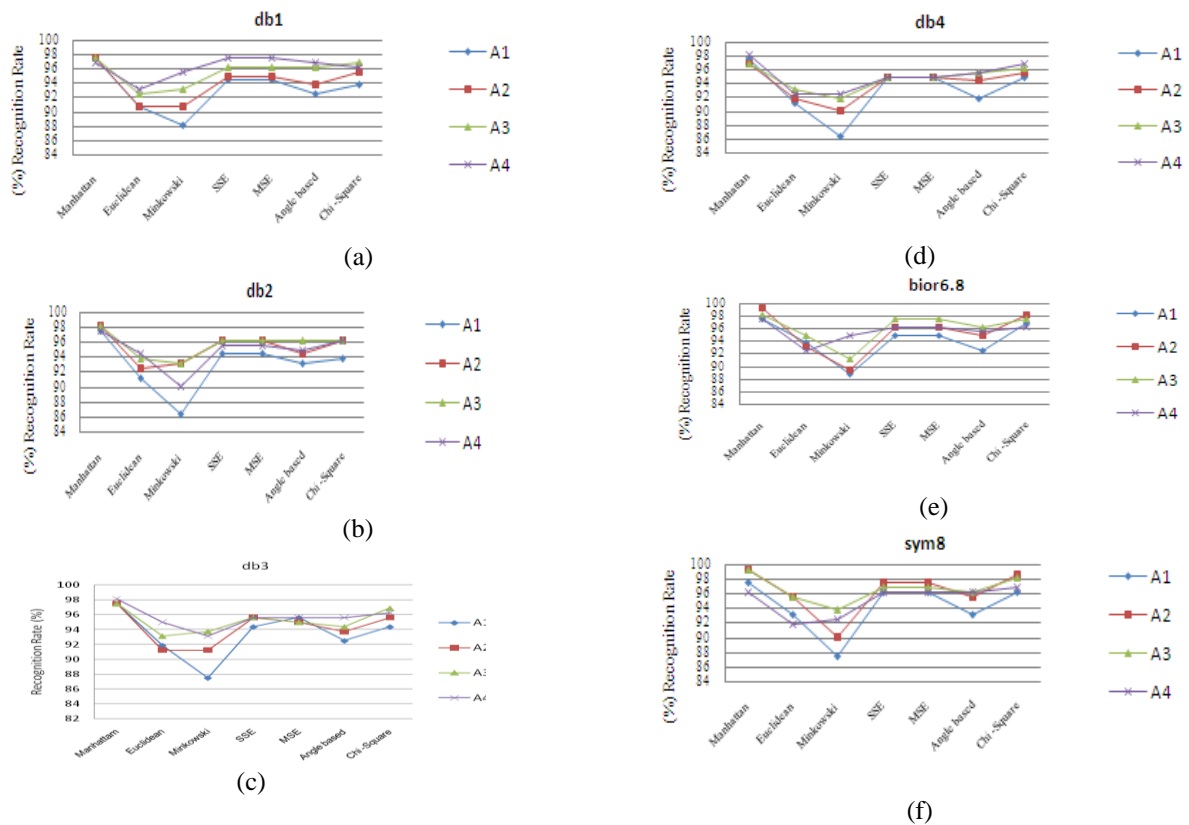


Figure 6. (a) to (f) Recognition rates for different wavelet using distance measures

VI. CONCLUSION

In this paper we compared 7 distance measures using four level decomposition of six different wavelet transforms for face recognition. ORL database is used for experiments. Recognition experiments were performed using the database containing images of 40 persons (40 x 10=400). The experiments showed that the best recognition results are achieved using Manhattam distance measure on A2 and A3 subbands of symlets 8 wavelet.

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