International Journal of Research in Advent Technology, Vol.4, No.7, July 2016
E-ISSN: 2321-9637
Available online at www.ijrat.org

A Robust Method for Multimodal Face Recognition using 2DPCA, DCT and Polynomial Coefficients

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Abstract- In this paper, an efficient approach is used for face recognition. Here both 2D and 3D face recognition is done. A novel method for feature extraction is used. Here it is done using Two Dimensional Principal Component Analysis (2DPCA) and Polynomial Coefficients. Then these features are spectrally transformed using Discrete Cosine Transform (DCT). The spectrally transformed features of depth image using 2DPCA and Polynomial Coefficients are combined together at the score level. Similarly it is done in texture image. Then the final score fusion of depth image and texture image are combined which gives better results than they are used separately.

Index Terms- Depth, Texture, 2DPCA, Polynomial Coefficients, Discrete Cosine Transform (DCT)

1. INTRODUCTION

3D face recognition is one of the fastest growing research areas in pattern recognition. It overcomes the disadvantages of 2D face recognition such as illumination changes, pose variations, occlusion etc. The performance of a face recognition system can be improved by considering some additional features with texture image. Such types of recognition system where multiple features are used for identification is called multimodal face recognition systems. In the proposed method both texture (2D) image and depth (3D) image are considered. Depth is invariant to physical changes and provides recognition in different view angles. Preprocessing is done to remove noise from the input texture image using Wiener filter. It is not done in depth image since depth is invariant to noise. Then features are extracted from the input texture and depth images using 2DPCA and Polynomial Coefficients. Then these features are spectrally transformed using DCT. Finally classification is done using Euclidean distance classifier.

Most of the earlier works in feature extraction is done by different methods which include Principal Component Analysis (PCA), Two Dimensional PCA (2DPCA), Independent Component Analysis (ICA), Local Binary Pattern (LBP), Linear Discriminant Analysis (LDA) etc. One of the earlier methods in feature extraction was proposed by Mathew Turk and Alex Pent land [1] using Eigen faces, an approach that uses PCA. It was based on decomposing face images into a set of characteristic feature images known as Eigen faces. In PCA based approach the 2D image is transformed into 1D image vector. The size of covariance matrix of 1D image vector will be larger. In order to overcome this dimensionality reduction problem Jian Yang [3] proposed a new method called two dimensional PCA (2DPCA). In this method image matrix is not transformed into 1D image vector. So the size of covariance matrix is small when compare to the size of covariance matrix of the conventional PCA.

2. PROPOSED METHOD

The detailed explanation of the proposed method is explained below. The block diagram of the proposed method is shown in fig 3. Initially preprocessing is done using Wiener filter to remove noise from the input texture image.

2.1 Feature Extraction

Consider the face image database FRAV3D [4], contains M images. Each face image in the database is of same size. The database contains both texture image and depth image. Here we have M different persons with N samples each. The main task in this method is to check the similarity between the reference and test image. Feature extraction is done in both texture image and depth image. Here 2DPCA and Polynomial Coefficients are used for feature extraction. After extracting the features using 2DPCA it is reshaped into 1D since Polynomial

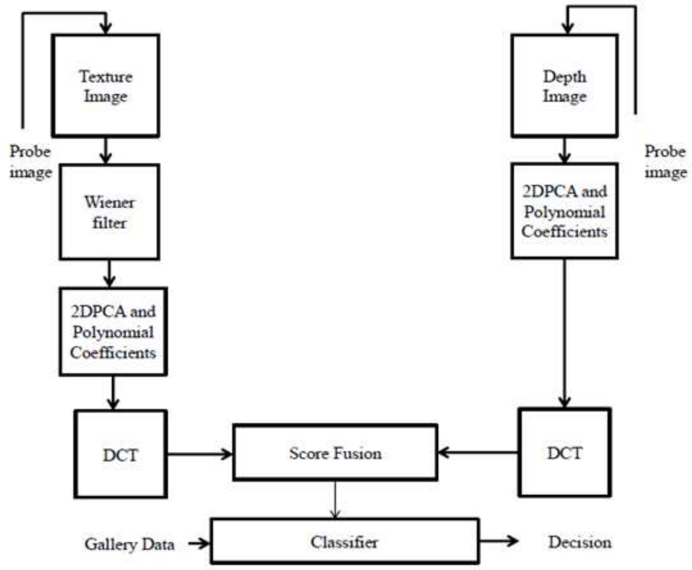

Figure 1: Block Diagram of the proposed method

Coefficient is 1D. These coefficients are directly calculated from the face images. It represents the important features of images.

Algorithm for feature extraction

Step 1: Obtain the depth images A_1, A_2…..A_i. Let N represents number of samples. First consider 2DPCA

Step 2: Compute mean of depth images

$$A_m = \frac{1}{N}\sum_{i=1}^{N} A_i \quad (1)$$

Step 3: Compute Standard Deviation

$$A_{SD} = \sum_{i=1}^{N} (A_i - A_m) \quad (2)$$

Step 4: Compute Variance

$$A_{VAR} = A_{SD}^{T} * A_{SD} \quad (3)$$

Step 5: Compute Covariance

$$A_{COV} = A_{VAR} / N \quad (4)$$

Step 6: Compute Eigen vectors (X_1 ,X_2……. X_n) and Eigen Values (λ_1, $\lambda 2$………. λ_n) of covariance matrix.

Step 7: Compute Polynomial Coefficients P(C) from the depth images.

$$P(C) = \lambda^{n} - c_n\lambda^{n-1} - c_{n-1}\lambda^{n-2} \ldots.. - c_1 \quad (5)$$

where c_n,c_{n-1}, ……c_1 represents the Polynomial Coefficients

Step8: Similarly repeat the steps from 1 to 7 for texture image feature extraction.

These features have some redundant information which can be removed using spectral transform. Here in this method DCT is used as the spectral transform tool to remove the redundancy. The equation for DCT [8] is given by,

$$F(u, v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y) \cos\frac{(2x+1)\pi u}{2M} \cos\frac{(2y+1)\pi v}{2N} \quad (6)$$

For m x n image.

2.2 *Fusion of Features*

Fusion of features involves combining the results of 2DPCA and Polynomial Coefficients. Here error values are obtained for texture and depth image using the two methods. The equations below shows the fusion of features given by,

$$d_{2D} = w\_t * t_{2DPCA} + (1-w\_t) * t_{Poly} \quad (7)$$

$$d_{3D} = w\_d * d_{2DPCA} + (1-w) * d_{Poly} \quad (8)$$

$$D = w * d_{2D} + (1-w) * d_{3D} \quad (9)$$

where d_{2D} represents the fusion of texture, w_t represents weight vector of texture its value is 0.9, t_{2DPCA} represents the error values of texture obtained by using 2DPCA, t_{Poly} represents the error values of texture obtained by Polynomial Coefficients.d_{3D} represents fusion of depth, w_d represents weight vector of depth its value is 0.95, d_{2DPCA} represents the error values of depth obtained by using 2DPCA, d_{Poly} represents the error values obtained by using Polynomial Coefficients. D represents the final fusion of texture and depth and w represents the weight vector of final fusion its value is 0.3.

2.3 *Classification*

After collecting the scores from depth image and texture image the next stage is classification. The function of classifier is to group the unknown images. In this method, classification is done with the widely used Euclidean distance classifier. It examines the root of square differences between the coordinates of a pair of images. If the distance is minimum then the images compared are similar otherwise not similar. Euclidean distance classifier is given by equation,

$$d(x, y) = \sqrt{\sum_{i=1}^{k}(xi - yi)^2} \quad (10)$$

where x_i represents reference image and y_i test image.

3. FACE DATABASE

In this proposed method a multimodal database called FRAV3D database is used. It has been acquired using 105 volunteers. A scanner MINOLTA VIVID-700 red laser light stripe triangulation rangefinder was used under controlled indoor condition. It consists of approximately one woman after three men. Here a total of 16 samples per person are considered in every session, with different poses and lighting conditions. The database consist of texture image (2D), range image (2.5D) and depth image (3D). So it is called as a multimodal database. Figure 4 shows the examples of FRAV3D database, where gray scale image is the texture image and the other is depth image.

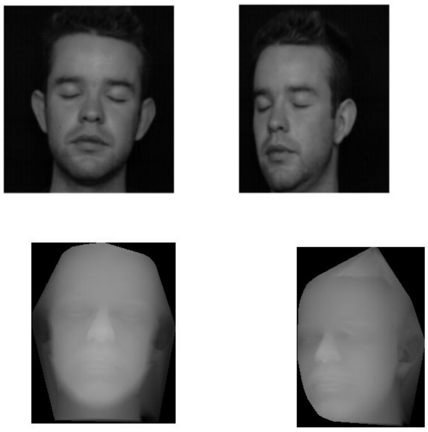

Fig 4: Examples of FRAV3D database

4. EXPERIMENT AND RESULTS

The proposed system is evaluated using MATLAB R2013a. For testing and analysis FRAV3D database is used. In this proposed method 1000 samples are taken for testing and 100 samples for training with different pose variations. Here feature extraction is done in two ways using 2DPCA and Polynomial Coefficients in both texture and depth. Then the features are spectrally transformed. DCT is used as the spectral transform tool. Finally fusion is done.

Table I shows the accuracy of the proposed face recognition using texture only. For 400 samples accuracy of texture using 2DPCA spectrally transformed by DCT is 82.25% and with Polynomial Coefficients spectrally transformed by DCT is 46% and accuracy of fusion is 83%. From this it is clear that fusion has more accuracy than the individual accuracies of 2DPCA and Polynomial Coefficients. Table II shows the accuracy of the proposed face recognition using depth only. Table III shows the accuracy of fusion of depth and texture. Here for 1000 samples accuracy of depth is 36.80%, texture is 50.70% and fusion is 52.90%. From this it is clear that multimodal fusion is having better results than the individual results of depth information and texture information.

TABLE I: ACCURACY OF FACE RECOGNITION USING TEXTURE ONLY

No of Samples	**Accuracy (%)**		
	2DPCA Texture	***Polynomial Coefficients Texture***	***Fusion***
400	82.25	46.00	83.00
500	72.20	37.40	73.00
600	63.16	32.50	64.50
700	61.00	29.28	62.00
800	59.50	26.75	60.25
900	53.55	24.22	54.55
1000	49.90	22.00	50.70

TABLE II: ACCURACY OF FACE RECOGNITION USING DEPTH ONLY

No of Samples	**Accuracy (%)**		
	2DPCA Depth	***Polynomial Coefficients Depth***	***Fusion***
400	70.50	43.50	71.25
500	57.80	35.60	58.60
600	49.50	30.50	50.33
700	45.85	26.85	46.71
800	42.75	24.50	43.62
900	38.11	21.77	39.00
1000	35.00	19.70	36.80

TABLE III: ACCURACY OF FUSION

No of Samples	Accuracy (%)		
	Depth	*Texture*	*Fusion*
400	71.25	83.00	86.25
500	58.60	73.00	74.00
600	50.33	64.50	65.50
700	46.71	62.00	63.71
800	43.62	60.25	62.12
900	39	54.55	56.00
1000	36.80	50.70	52.90

Figure 5 shows the comparison of depth, texture and fusion. From the fig it is shows that fusion is having more accuracy.

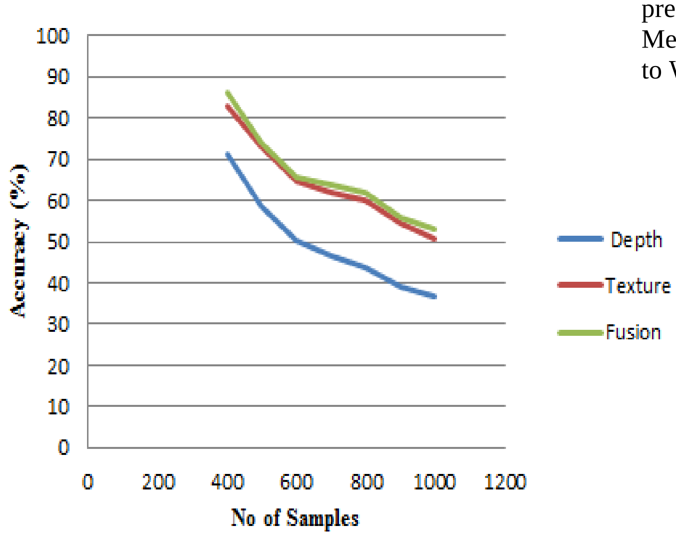

Fig 5: Comparison of Fusion using DCT

In order to evaluate the performance of DCT another spectral transformation tool Discrete Fourier Transform (DFT) is used instead of DCT in the proposed method. Table IV shows the accuracy of fusion using DCT and DFT. It shows that DCT is better for the proposed method than DFT.

TABLE IV: COMPARISON OF FUSION USING DCT AND DFT

No of Samples	Accuracy (%)	
	With DCT	*With DFT*
400	86.25	84.75
500	74.00	71.40
600	65.50	63.16
700	63.71	61.42
800	62.12	60.00
900	56.00	54.11
1000	52.90	49.80

Figure 6 shows the comparison of fusion using DCT and DFT. Table V shows the comparison of Wiener filter and Median filter. We had preprocessed the input image of texture using Median filter but it is not efficient when compared to Wiener filter.

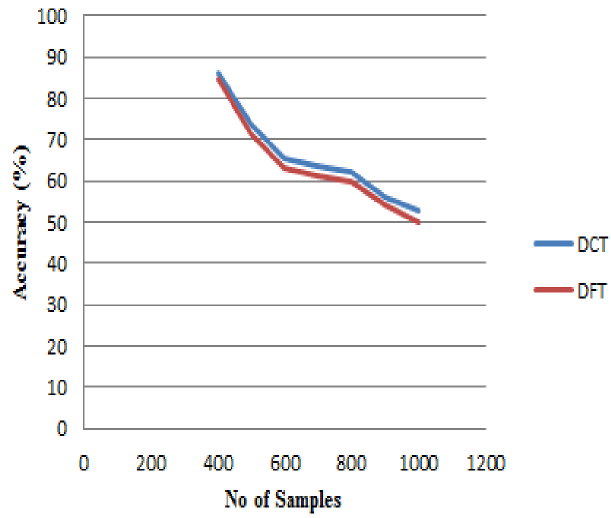

Fig 6: Comparison of Fusion using DCT and DFT

TABLE V: COMPARISON OF WIENER AND MEDIAN FILTER

No of Samples	Accuracy (%)	
	Wiener filter	***Median filter***
400	86.25	85.50
500	74.00	72.40
600	65.50	64.50
700	63.71	62.14
800	62.12	60.75
900	56.00	54.88
1000	52.90	51.90

5. CONCLUSION

In this proposed method a novel approach is proposed for feature extraction that is, combining 2DPCA and Polynomial Coefficients. Here preprocessing is done in texture image only. We had used two filters for preprocessing Wiener and Median. From the observations we had concluded that Wiener filter is efficient for our method. Then after extracting the features they are spectrally transformed. Here we used DCT and DFT as spectral transform tool. From the observation, we had concluded that DCT is efficient for features that had extracted using 2DPCA and Polynomial Coefficients than DFT. Then fusion is done, from observation combining texture and depth at the score level gives better accuracy than they are separately used.

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