Multimodal Face Recognition using Spectral Transformation by LBP and Polynomial Coefficients

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***Abstract*—This paper presents a multimodal face recognition using spectral transformation by Local Binary Pattern (LBP) and Polynomial Coefficients. Here 2D image and 3D image are combined to get multimodal face recognition. In this method a novel feature extraction is done using LBP and Polynomial Coefficients. Then these features are spectrally transformed using Discrete Fourier Transform (DFT). These spectrally transformed features extracted from texture image using the two methods are combined at the score level. Similarly this is done in depth image. Finally feature information from texture and depth are combined at the score level which gives better results than the individual results.**

***Index Terms*—Texture, Depth, Local Binary Pattern (LBP), Polynomial Coefficients, Multimodal, Discrete Fourier Transform (DFT)**

I. INTRODUCTION

Face Recognition is a process in which an unknown image is a matched with a known image from the database. It is one of the most extensively researched topics in image analysis because of its wide range of applications. A face recognition system consists of face detection, feature extraction and finally recognition. Face recognition is classified into two; 2D face recognition and 3D face recognition. In 2D face recognition two dimensional geometry of face is used whereas in 3D face recognition three dimensional geometry of face is used. Nowadays 3D face recognition has attracted researchers due to its wide range of applications. It overcomes the problems caused by 2D face recognition that is, illumination changes, pose variations, occlusion etc.

The feature extraction can be done in several methods such as Principal Component Analysis (PCA), Two Dimensional PCA (2DPCA), Independent Component Analysis (ICA), Local Binary Pattern (LBP), Linear Discriminant Analysis (LDA) etc. One of the turning point in face recognition was the Eigen faces [1], proposed by Mathew Turk and Alex Pentland. It is one of the earlier approaches in feature extraction that uses PCA. Another method of feature extraction used in face recognition is LBP proposed by Ojala [8]. In this method input face image is divided into small regions from which features are extracted. These features consist of binary patterns that describe the neighboring pixels of the image.

In this paper a face recognition method is proposed using both 2D image (texture) and 3D image (depth). The advantage of using depth image is that, features can be easily extracted from the raw data which allows fast processing. Depth is an important feature which is invariant to physical changes and provides recognition in different view angles. Initially preprocessing is done to remove noise from the input texture images. Then feature extraction is done by using LBP and Polynomial Coefficients [6]. Then to remove redundant information from the features spectral transformation is done using DFT. Finally to get a multimodal face recognition system the feature information from depth image and texture image are combined which gives better results than they are used separately.

II. PROPOSED METHOD

The block diagram of the proposed method is shown in Fig. 3. The proposed algorithm aims at extracting features from the input images and fuses score to get better results. Preprocessing is the first stage in the proposed method. It is done only in texture image using Wiener filter. Since depth is invariant to noise preprocessing is not required. Fig. 1 shows the texture image from the data base and Fig. 2 shows the preprocessed texture image using Wiener filter.

Fig. 1. Texture image from the database

Fig. 2. Preprocessed Texture image using Wiener filter

A. Feature Extraction

In this method features are extracted using Local Binary Pattern (LBP) and Polynomial Coefficients. In LBP method, each pixel from the input image is compared with its eight neighbors in a 3x3 neighborhood by subtracting the center pixel value. If the neighboring pixel has a greater value than the center pixel then it is assigned as 1 otherwise 0. Thus by combining these binary values a binary number is obtained, which is referred as Local Binary Patterns. The equation for LBP is given by,

$$LBP_{U,V}(x,y)=\sum_{i=0}^{N-1} s(b_i-b_c)2^i,\ s(x)=\begin{cases} 1\ if\ x \geq 0 \\ 0\ otherwise \end{cases} \quad (1)$$

where b_c is the value of center pixel and b_i is the value of the surrounding pixel, (U,V) denotes the neighborhood of U sampling points on a circle of radius V. Then features are extracted using Polynomial Coefficients. These coefficients are directly calculated from the input images. It represents the important features of the image. The equation for Polynomial Coefficients P (C) is given by,

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

where c_n, c_{n-1}, ….. c_1 represents the Polynomial Coefficients and λ represents the eigen value of the input image.

These extracted features are spectrally transformed using the transformation tool DFT. The better energy compaction and rotation invariance property of DFT increases the accuracy rate of the system.

B. Fusion of Features

Fusion of features involves combining the results of LBP and Polynomial Coefficients which increases the final accuracy than the individual accuracies. Here error (score) values are obtained for texture and depth images using both LBP and Polynomial Coefficients. The equation for fusion of features is given by,

$$d_{2D}=w\_t * t_{LBP} + (1-w\_t) * t_{Poly} \quad (3)$$

$$d_{3D}=w\_d * d_{LBP} + (1-w\_d) * d_{Poly} \quad (4)$$

$$D=w * d_{2D} + (1-w) * d_{3D} \quad (5)$$

where d_{2D} represents the fusion of texture, w_t represents weight vector of texture, t_{LBP} represents the error values of texture obtained by LBP, 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, d_{LBP} represents the error values of depth obtained by LBP, d_{Poly} represents the error value of depth obtained by Polynomial Coefficients. D represents the final fusion of texture and depth and w represents the weight vector of final fusion. The value of weight vectors are obtained by trial and error method.

C. 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,

$$d\ (x, y) = \sqrt{\sum_{i=1}^{k}(xi-yi)^2} \quad (6)$$

where x_i represents reference image and y_i test image.

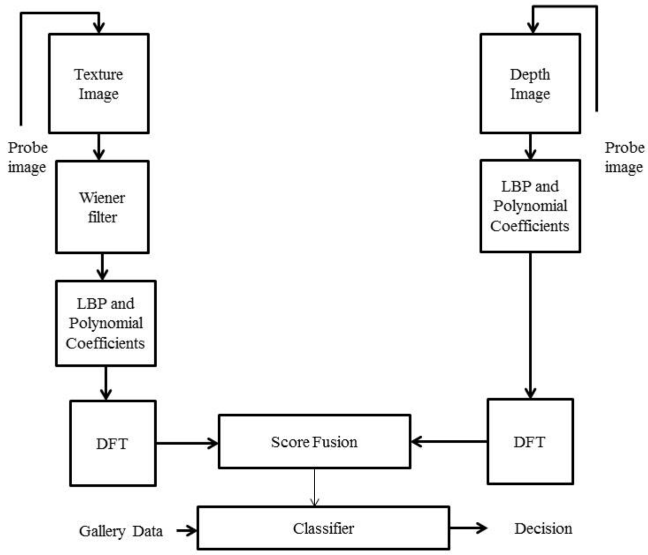

Fig. 3. Block Diagram of Proposed Method

The database used here is FRAV3D [4], which is a multimodal database. It consists of texture image (2D), range image (2.5D) and depth image (3D). There are 105 volunteers each person with 16 samples. Fig. 4 shows the examples of depth image from the database.

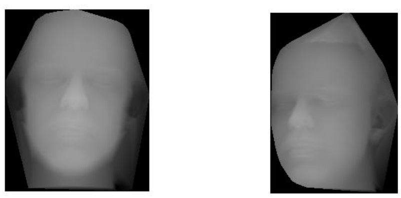

Fig. 4. Examples of FRAV3D database

III. EXPERIMENT AND RESULTS

The proposed system is evaluated using windows 8.1 system with 4GB RAM and Intel-i3 processor using MATLAB R2013a. For testing and analysis FRAV3D database is used. In the proposed method 1000 samples are taken for testing and 100 samples for training. Here feature extraction is done in two ways using LBP and Polynomial Coefficients in both texture and depth. Then these spectrally transformed features are classified using Euclidean distance classifier.

Table I shows the accuracy of the proposed face recognition using texture only. From the observations it is clear that fusion of two feature extraction method is having better result than the individual results. Table II shows the accuracy of the proposed face recognition using depth only. Here also fusion of the matched scores gives better results. Table III shows the multimodal fusion that is, combining depth and texture information. From the observation for 400 samples accuracy of depth is 83.25%, texture is 94.50 % and fusion is 96.75%. It proves that the recognition accuracy rate of final fusion increases than that of separate accuracy of depth and texture.

TABLE I: ACCURACY OF TEXTURE

No of Samples	**Accuracy (%)**		
	LBP Texture	***Polynomial Coefficients Texture***	***Fusion***
400	94.25	45.50	94.50
500	83.00	36.80	83.60
600	76.50	30.83	76.83
700	76.42	26.85	77.14
800	74.75	24.00	75.25
900	67.11	21.33	67.66
1000	62.30	19.30	62.90

TABLE II: ACCURACY OF DEPTH

No of Samples	**Accuracy (%)**		
	LBP Depth	***Polynomial Coefficients Depth***	***Fusion***
400	83.00	44.25	83.25
500	72.60	36.20	73.00
600	68.33	31.00	68.66
700	68.71	27.42	68.85
800	68.62	24.62	68.75
900	62	22.00	62.33
1000	57.70	19.90	57.90

TABLE III: ACCURACY OF FUSION

No of Samples	**Accuracy (%)**		
	Depth	***Texture***	***Fusion***
400	83.25	94.50	96.75
500	73.00	83.60	86.80
600	68.66	76.83	83.00
700	68.85	77.14	82.14
800	68.75	75.25	80.87
900	62.33	67.66	73.00
1000	57.90	62.90	68.50

Fig. 5 shows the comparison of depth, texture and fusion from Table III. From the graphical representation it shows that fusion is having more accuracy.

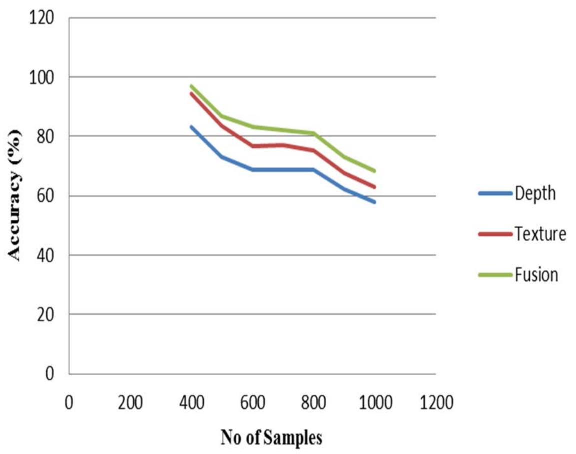

Fig. 5. Comparison of depth, texture and fusion

In order to evaluate the performance of DFT another spectral transformation tool Discrete Cosine Transform (DCT) is used instead of DFT in the proposed method. Table IV shows the final fusion of depth and texture using DFT and DCT. From the observation, DFT is having higher accuracy than DCT for the combination of feature extraction using LBP and Polynomial Coefficients.

TABLE IV: COMPARISON OF FUSION USING DFT AND DCT

No of Samples	**Accuracy (%)**	
	With DFT	***With DCT***
400	96.75	90.25
500	86.80	81.40
600	83.00	77.83
700	82.14	77.71
800	80.87	76.50
900	73.00	69.00
1000	68.50	64.00

Fig. 6 shows the graphical comparison of final fusion of depth and texture using DFT and DCT.

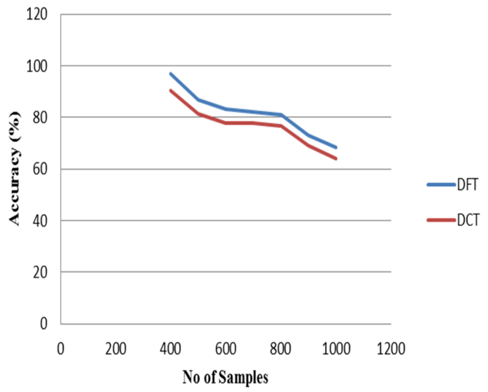

Fig. 6. Comparison of final fusion of depth and texture using DFT and DCT.

Table V shows the reliability analysis of face recognition rates. Here TAR stands for True Acceptance Rate, TRR for True Rejection Rate, FAR for False Acceptance Rate and FRR for False Rejection Rate. Here 50 samples are used for reliability analysis. From the observation TAR for fusion is 100% and FAR is 8% that is, FAR is decreased when compared to the individual rates of depth and texture. A reliable system should have maximum TAR and FRR while maintain minimum FAR and TRR.

TABLE V: RELIABLITY ANALYSIS

	TAR (%)	**TRR (%)**	**FAR (%)**	**FRR (%)**	**Threshold**
Depth	94.00	6.00	82.00	18.00	2.80
Texture	100.00	0	10.00	90.00	4.70
Fusion	100.00	0	8.00	92.00	4.09

IV. CONCLUSION

In this method a novel feature extraction method is used by combining LBP and Polynomial Coefficients. Then these features are spectrally transformed using DFT. From the proposed method combination of two feature extraction methods gives better accuracy than their individual accuracies. Also the spectral transform tool DFT is having better results for the combination of LBP and Polynomial Coefficients than using DCT. The spectral transformation and preprocessing of the input texture images improves the recognition accuracy of the system.

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REFERENCES

[1] Mathew Turk and Alex Pent land, ―Eigen faces for Recognition, Journal of Cognitive Neuroscience Volume 3, Number 1(1991).
[2] P.N. Belhumeur, J.P. Hespanha, D.J.Kriegman, ―Eigen faces vs.Fisher faces : recognition using class specific linear projection, IEEE Trans. Pattern Anal. Mach. Intell.(1997)

[3] W.Zhao, R.Chellappa,P. J.Philips, A.Rosenfeld, Facerecognition: A literature survey,ACMComput.Surv.35(4)(2003)399–458.

[4] http://www.frav.es/databases/FRAV3D

[5] Naveen S, Dr R S Moni - Multimodal Approach for Face Recognition using 3D-2D Face Feature Fusion, International Journal of Image Processing (IJIP), Volume (8) : Issue (3) : 2014

[6] Vilas H. Gaidhane, YogeshV.Hote , Vijander Singh, An efficient approach for face recognition based on common eigenvalues, PatternRecognition47(2014)1869–1879

[7] Ahalya R K, Naveen S, Dr R S Moni, Multimodal Face Recognition System using Polynomial Coefficients, Proceedings of the 2nd National Conference on Advances in Computational Intelligence and Communication Technologies (NCACICT-2016)

[8] Timo Ojala, Kimmo Valkealahti, Erkki Oja and Matti Pietikäinen - Texture Discrimination with Multidimensional Distributions of Signed Gray Level Differences

[9] Di Huang, Caifeng Shan, Mohsen Ardebilian, Yunhong Wang, and Liming Chen - Local Binary Patterns and Its Application to Facial Image Analysis: A Survey