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3D Face Fecognition using Fourier-Cosine Transform Coefficients Fusion

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Abstract: ***3D Face recognition has been an area of interest among researchers for the past few decades especially in pattern recognition. The main advantage of 3D Face recognition is the availability of geometrical information of the face structure which is more or less unique for a subject. This paper focuses on the problems of person identification using 3D Face data. Use of unregistered 3D Face data significantly increases the operational speed of the system with huge database enrolment. In this work, unregistered 3D Face data is fed to a classifier in multiple spectral representations of the same data. Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT) are used for the spectral representations. The face recognition accuracy obtained when the feature extractors are used individually is evaluated. Fusion of the matching scores proves that the recognition accuracy can be improved significantly by fusion of scores of multiple representations. FRAV3D database is used for testing the algorithm.***

Index Terms—Point Cloud, Rotation Invariance, Pose Correction, Depth Map, Spectral Transformations, and Principal Component Analysis.

I.INTRODUCTION

3D Face recognition has been an active area of research in the past decades. The complications encountered in the enrollment phase and the huge computational requirements in the implementation phase have been the major hindrance in this area of research. The scenario has improved tremendously due to the latest innovations in 3D imaging devices and has made 3D Face recognition system a reliable option in security systems based on Biometrics. Though poor resolution is a major drawback encountered in 3D Face images the geometrical information present in 3D facial database can be exploited to overcome the challenges in 2D face recognition systems like pose variations, bad illumination, ageing etc. In this work, focus is made on an identification problem based on 3D Face data using fusion schemes. Identification corresponds to the person recognition without the user providing any information other than the 3D facial scan. The system arrives at an identity from among the enrolled faces in the database. Alexander M. Bronstein, Michael M. Bronstein and Ron Kimmel [2] proposed an idea of face recognition using geometric invariants using Geodesic distances. C. Beumier [3] utilized parallel planar cuts of the facial surfaces for comparison. Gang Pan, Shi Han, Zhaohui Wu and Yueming Wang [4] extracted ROI of facial surface by considering bilateral symmetry of facial plane.

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Xue Yuan, Jianming Lu and Takashi Yahagi [5] proposed a face recognition system using PCA, Fuzzy clustering and Parallel Neural networks. Trina Russ et al [6] proposed a method in which correspondence of facial points is obtained by registering a 3D Face to a scaled generic 3D reference face. Ajmal Mian, Mohammed Bennamoun and Robyn Owens [7] used Spherical Face Representation for identification. Ondrej Smirg, Jan Mikulka, Marcos Faundez-Zanuy, Marco Grassi and Jiri Mekyska [8] used DCT for gender classification since the DCT best describes the features after de-correlation. HuaGao, Hazım Kemal Ekenel, and Rainer Stiefelhagen[9] used Active Appearance model for fitting faces with pose variations. Mohammad Naser, Moghaddasi Yashar Taghizadeganand Hassan Ghassemian [10], used 2D-PCA for getting the feature matrix vectors and used Euclidean distance for classification., Omid Gervei, Ahmad Ayatollahi, and Navid Gervei[11] proposed an approach for 3D Face recognition based on extracting principal components of range images by utilizing modified PCA methods namely 2D-PCA and bidirectional 2D-PCA.

A typical 3D Face is shown in Fig.1. Fig.2 represents its axis level representation.

Fig 1:3D Face Model

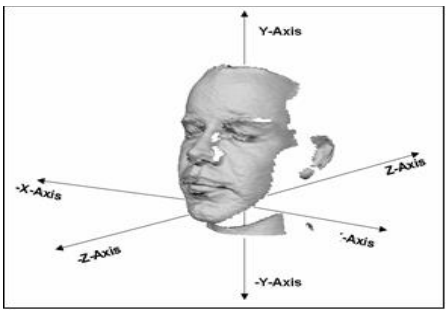

Fig 2: 3D Face in Space

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First thefusion of the representative transformations from 3D to 1D space and 3D to 2D space is considered. Since only a sparse set of points in the 3D point cloud are available, it is necessary to increase the data density by using multiple data representations. For this the data is transformed into spectral domain using DFT and DCT. This sparse set of data with occlusion can be effectively countered by invoking multiple score fusion schemes which can effectively improve the feature data density.

Section II deals with the proposed scheme which covers the 3D to 1D and 2D dimensional reduction and its spectral transformation and section III analyses and describes the results of fusion schemes using the experimental results of individual schemes and fusion schemes.

II.PROPOSED IDEA FOR FACE RECOGNITION

The system aims at extracting the feature from the input data through multiple feature extraction tools and fuses the scores to get a system with better recognition accuracy. The main feature extraction principle used in this system is the spectral transformation. The spectral transformation tools used here are 1D-DFT and2D-DFT along with 2D-DCT.These spectral transformations transform the data to a better representation which increases the accuracy of recognition systems.

The most important part of this work lies in the pattern classification problem. A pattern of data points is available. This pattern is not sufficient for the recognition system to work since the data will be highly occluded due to pose variations in the X, Y and Z axis.

The 3D Face recognition scheme is affected by pose variations of the subject. There are methods available in which the correction to this effect of pose variations also is included. One such method is the Iterative Closest Point (ICP) algorithm. But the main disadvantage of these methods is that a reference face is to be used as a model for other rotated faces to be corrected. Also the processing time taken is very high. Further, the reliability of this result depends on the accuracy in selection of the reference face model used. Therefore, in this work done, this correction to the effect of pose variation is not considered. The method aims at recognizing the subject without much computationally complex mathematical procedure. Also the results prove that the efficiency of system is comparable with a system with pose correction. The idea behind spectral representation of data is that, when data is in spatial domain, comparison will be done as one to one pixel level or voxel level. So the rotation and translation of data will highly affect the result. Moreover the accuracy of the system will go down to even 5% under severe pose variations in X, Y axis. When spectral transformation is done the distributed data will be concentrated or it may be represented in a more uniform way. I.e. the input data will be concentrated and represented uniformly in spectral domain. The translation and rotation invariance properties of the transformations used will aid to improve the accuracy of system significantly.

The data available for the analysis and testing will be in Point Cloud format which is a matrix array of size Mx3. The value of M denotes the number of points in the 3D space. For each data input the number of points used will be different for representation. An optimum number of points are selected for Point Cloud data vector.

The proposed method involves the following steps given below in sequence. First is the conversion of Point Cloud data to Euclidean Metric form and take its DFT to get its spectral representation. Second step is to map the 3D points to 2D grid without pose correction to get the depth map. From this 2D depth map nose tip is detected using Maximum Intensity Method and the area around the nose (ROI-Region of Interest) is extracted (Fig.4 and Fig.5). On this ROI data 2D-DFT and 2D-DCT is applied. The detailed explanations are given on sections A, B and C. Once spectral representations are obtained, Principal Component Analysis (PCA) is applied on that data to get the corresponding weight vectors. This weight vectors are fed to a classifier which uses Euclidean distance for classification. Explanation regarding this is given on section D and E respectively.

A. Point Cloud representation as a One Dimensional Vector

This M x 3 points are converted to an M x1 vector using Euclidian metric transformation. This reduced the number of points under consideration to M while the original being 3M. This also aids the real time implementation of the system faster. For finding the Euclidean distance, the relative difference between the Z coordinate and the X, Y coordinates are taken.

$$\text{Euclidian Metric}=\sqrt{(Z-X)^2+(Z-Y)^2} \qquad (1)$$

The Euclidean Metric data will be distributed in spectral domain as shown in Fig.3. It relate to the data for a particular axis and orientation. The data distribution is different for different axis at different orientation. But when DFT is computed, it turns out that the data distribution becomes similar. This significantly will improve the recognition accuracy. The reason for choosing DFT over DCT which has a better energy compaction property is that with DCT, the recognition accuracy with X axis and Y axis rotation has been found to be almost half of that obtained using DFT. However along Z orientation, this use of DCT has been found to give better recognition accuracy.

Transformation of Euclidean Metric data to spectral domain can be done using 1D-DFT, using equation (2).

$$F(K)=\sum_{n=0}^{N-1} f(n)e^{-j2\pi Kn/N} \text{ , for a vector of size Nx1} \qquad (2)$$

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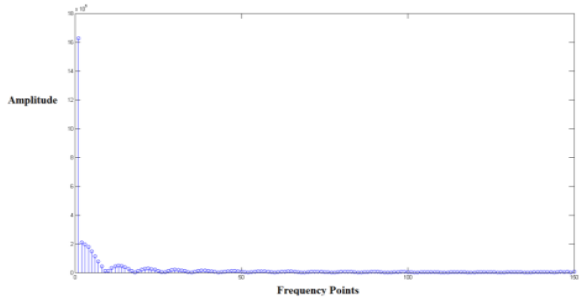

Fig 3: Euclidean Metric in Spectral Domain

The Table1 shows the improvement obtained when DFT is used over DCT. It can be seen that for X axis with 50o pose variations, 100% improvement in accuracy is obtained. The maximum accuracy of Y axis 20o pose variation is about 56%.

TABLE I : DFT-DCT COMPARISON OF RECOGNITION RATE

Rotation in Degree	Y Axis		DFT over DCT %	X Axis		DFT over DCT %
	DFT	DCT		DFT	DCT	
	FRR (%)	FRR (%)		FRR (%)	FRR (%)	
+5,-5	79.00	75.00	5.33	86.50	72.50	19.31
+10,-10	56.00	46.00	21.74	66.50	45.00	47.78
+15,-15	40.50	31.50	28.57	50.00	29.00	72.41
+20,-20	27.50	23.00	19.57	40.00	21.50	86.05
+25,-25	22.00	20.00	10.00	38.00	19.00	100.00

B. Nose tip Localization and face area extraction

For localizing the nose tip, maximum intensity method is used. In this method assumption is made that the nose tip will be the point with maximum pixel intensity. Once the nose tip is found the circular area (ROI) around the nose tip is extracted using an optimum radius. Now the depth map will contain the face area only, all other unwanted portions are cropped away. Next face area is centralized by making the nose tip as the center pixel of the image. Otherwise the matching process will result in a lower accuracy. The face area is also normalized by the maximum intensity. The centralized face image is as shown in Fig.4 and Fig.5.

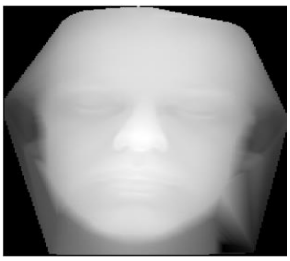

Fig 4: Depth Map **Fig 5: ROI from Depth Map**

C. Use of 2D DFT and 2D DCT

The point cloud data in 3D space is projected to an X-Y grid to get 2.5D (2.5D image is the depth map itself) image using standard projection formula. This depth data will be having the pixel value as the Z- Coordinate of Point Cloud data. Face images have higher redundancy and pixel level correlation which is a major hindrance in face recognition systems. Transforming face images to spectral domain will reduce the redundancy. Here only the magnitudeof spectral data is taken alone since it is not transformed back to spatial domain in any of the processing stages. Now, the Depth image is transformed to spectral domain using 2D-DCT. The energy compaction will take place and the result will be again an M x N matrix. The result is shown in Fig.6. Here the global feature extraction by DCT is made used of. DCT has the property of de-correlation which enables the data structure to lose spatial pixel dependency. The low frequency components which mainly form the facial features will be prominent in the transformed space which makes the pattern classification more reliable, since the human eyes are more sensitive to information in low frequency spectrum. Transformation to spectral domain using 2D-DCT can be done using equation (3) and the transformed image is shown in Fig.6.

F(u,v)=

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

for a M x N depth image.(3)

Again the depth image is transformed using 2D-DFT so that rotation effects are reduced. Face images with some orientations in the spatial domain are used as test data. DFT is a rotation invariant transformation. So that the distribute pixel values (normalized) are properly aligned which enables the pattern matching more efficient.DFT spectrum of face image will appear as shown in Fig.7.Transformation to spectral domain using 2D Discrete Fourier Transformation can be done using equation (4).

F(U,V)= $\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)e^{-j2\pi(Ux/M+Vy/N)}$, for a M x N depth image (4)

Now the error score is estimated using all the multiple representations separately. For processing Euclidean metric, 1D-PCA is used and for processing 2D DCT and 2D DFT representation 2D-PCA is used. 1D-PCA was also used for the 2D representations but 2D-PCAgave better result for 2D representations.

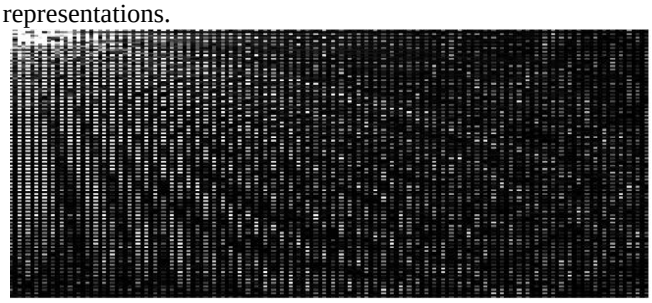

Fig 6: DCT Representation of ROI Depth Map

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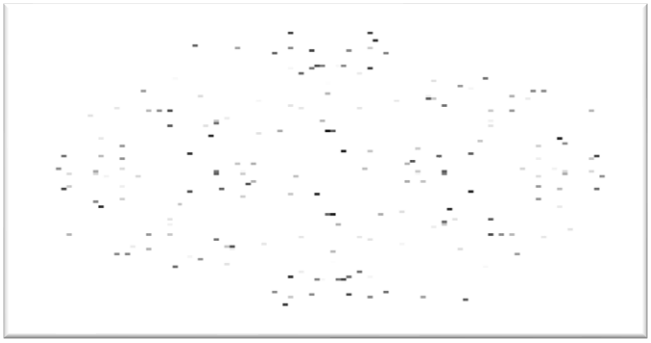

Fig 7: DFT Representation of ROI Depth Map

D. Principal Component analysis

Use of spectral transformations will make the data samples almost uncorrelated. Even then, some spatial dependency may exist. So Principal Component Analysis (PCA)[12] is used for the correlation process as it uses orthogonal transformations to get linear uncorrelated data sets called principal components. Conventional covariance method for the calculation of principal components is used here. Feature extraction using 1D-PCA is done as follows. Let Xi be the spectral transformed 1D Euclidean Metric which represents i^{th} person, it is grouped as a M x N matrix $X=[X_1\ X_2 \ldots X_N]$, where N is the number of face samples under consideration. Mean vector is calculated as follows

$$X_m=\frac{1}{N}\sum_{i=1}^{N} X_i \qquad (5)$$

Standard deviation will be calculated $X_{SD}=$

$$\frac{1}{N}\sum_{i=1}^{N}(X_i - X_m) \qquad (6)$$

Covariance matrix is calculated

$$X_{COV}=X_{SD}*X^T_{SD} \qquad (7)$$

This is a matrix of size M x M, which is of very large dimension. Also it gives M Eigen values and M Eigen vectors which are very large in number to process. The base idea of dimensional reduction by changing the construction of covariance matrix can be now used.

$$X_{COV}=X^T_{SD}*X_{SD} \qquad (8)$$

The result is a matrix of size N x N, where N is the number of subjects under consideration. It gives N Eigen values and N Eigen vectors. The Eigen values are sorted in descending order and will select the first N' largest Eigen values and corresponding Eigen vectors. Eigen vectors in N' dimension is transformed to the higher dimension of M by multiplying with Standard deviation Matrix. Now the test data is projected to this lower dimension space to get the corresponding weight vectors.

In 2D-PCA2D spectral representation of Depth map is considered. The only difference in calculating the Covariance matrix is that here a 2D matrix is used when compared to 1D Matrix in 1D-PCA.After determining the Eigen values and Eigen vectors a 2D weight vector matrix is obtained which is then converted to a column matrix.

E. Score Fusion

Error values are calculated for each data representations and all this error values are combined as a single error value using the linear expression as given in equation 9.

Error=W_DCT*Error_DCT+W_DFT*Error_DFT+ W_EDDFT*Error_EDDFT. (9)

On the equation 9 W_DCT is weight for error value obtained using 2D DCT and is taken as 1, W_DFT and W_EDDFT are weights for the error value obtained using 2D DFT and 1D DFT on depth map and Euclidean metric respectively. This weight values are selected in such way that the error values of 2D DFT and 1D Euclidean metric are in same scale as that of error value due to 2D DCT. Weight value can be approximated using equation10&11.

$$\frac{1}{W\_DFT}=\frac{Error\_DFT}{Error\_DCT}, \text{ rounded to } 10^{2}\text{'s.} \qquad (10)$$

$$\frac{1}{W\_EDDFT}=\frac{Error\_EDDFT}{Error\_DCT}, \text{ rounded to } 10^{8}\text{'s.} \qquad (11)$$

By iterative process optimum weight values are approximately obtained are 10^2 and 10^8respectively..

III.RESULTS

A. Results of Individual representation accuracy analysis

For analysis and testing FRAV3D database is used here. It contains 106 subjects. Of these 100 subjects were taken into consideration. Testing was done on the input data with rotation on X, Y and Z axis separately. For each degree of rotation 200 samples were tested and for each axis 1000 samples at+5°,-5°, +10°,-10°,+15°,-15 °,+20 °,-20 °,+25 ° and -25 ° pose variations were tested together. Comparison of the fusion scheme along with the direct 2D-PCA on depth data is also shown here. A substantial change in the recognition accuracy is observed. Table I shows the recognition accuracy obtained with different data representations when the pose variation is along X axis. Rotation in degree means the combined pose variation tested towards right and left direction. Here as the orientation increases the accuracy falls to a lower value when used as a single data representation. Similarly Table II and Table III denote the pose variations along Y and Z axis respectively. Here the recognition accuracy using feature vector using Euclidean representation maintains the accuracy minimum up

to 75% for Z axis (Ref Table III), 22% for Y axis (Ref Table II)

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TABLE II : For Rotation In X Axis With 10 To 50 Degree Variations

Rotation in Degree	R1 FRR %	R2 FRR %	R3 FRR %	R4 FRR %
+5,-5	55.00	86.50	65.50	85.50
+10,-10	20.50	66.50	15.50	36.00
+15,-15	6.00	50.00	6.00	10.50
+20,-20	4.00	40.00	5.50	3.50
+25,-25	4.50	38.00	5.00	4.50

TABLE III: For Rotation In Y Axis With 10 To 50 Degree Variations

Rotation in Degree	R1 FRR %	R2 FRR %	R3 FRR %	R4 FRR %
+5,-5	61.50	79.00	71.50	90.50
+10,-10	22.00	56.00	23.50	53.50
+15,-15	12.00	40.50	10.00	29.00
+20,-20	7.00	27.50	3.50	5.50
+25,-25	4.50	22.00	6.50	6.00

TABLE IV : For Rotation In Z Axis With 10 To 50 Degree Variations

Rotation in Degree	R1 FRR %	R2 FRR %	R3 FRR %	R4 FRR %
+5,-5	92.00	99.50	93.50	94.00
+10,-10	87.50	94.00	92.50	79.50
+15,-15	69.00	88.00	80.50	50.50
+20,-20	53.00	78.00	61.00	29.00
+25,-25	37.50	75.00	45.00	26.50

Where
R1-With 2D depth data using 2D-PCA,
R2-With 1D-PCA on Euclidean Metric,
R3-With 2D-PCA on DCT of Depth map,
R4-With 2D-PCA on DFT of Depth map

and 38% for X axis (Ref Table1). For 10º variations Z axis maintains accuracy above 90%, while other axis maintains above 55% only. Rotation in Y axis is the worst affected case since it will result in partial occlusion of data in the depth map.

For Z axis DCT seems to have improved recognition accuracy while for Y axis DFT has more accuracy. This is because of the lack of information due to the pose variations. So multiple data representations is used for improving the accuracy.

B. Results of Fusion Scheme analysis

The Table V shown below summarizes the results obtained by using fusion scheme. Accuracy of X axis pose variations ranges from 49% to 95.5% as shown in Table IV. With 50 º pose variation the geometric points are moved towards with 1 and 2 quadrants or 3 and 4 quadrants. Some face data near the jaw points are missing there in addition to the reduction in the projected area of nose tip and other geometric features. With 50 º pose variation along Y axis most of the area, nearly half of the face area is occluded. So the data set will be a sparse dataset, and the accuracy ranging from 40%to 98% (Ref Table IV) is obtained. In Z axis the data points will be completely redistributed, so that the spatial domain comparison will give an accuracy of nearly 38% for 50 º while the spectral domain representation fusion boosted it to 95%.

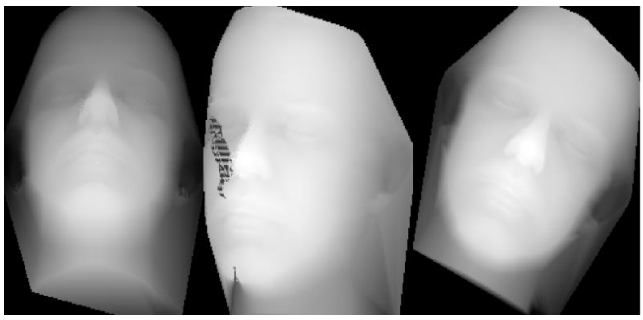

Fig 8: Depth Map with different pose variations along X, Y and Z axis.

TABLE V : Recognition Accuracy Of Fusion Scheme Compared With Individual Schemes.

Rotation in Degree	X-axis FRR%	Y-axis FRR%	Z-axis FRR%
+5,-5	95.50	98.00	99.50
+10,-10	82.50	93.00	99.00
+15,-15	65.50	83.00	98.50
+20,-20	52.50	65.00	97.50
+25,-25	49.00	40.00	95.00

C. Improvement in accuracy rates by Fusion Scheme

When the accuracy obtained in the fusion scheme is analyzed, the improvement in maximum accuracy for the Z-axis is about 1.27 for a single representation of data in spectral domain as shown in Table VI. But for Y axis it reaches a maximum of 2.36 and for X axis it is about 1.31 times.

TABLE VI : Improvement In Relative Recognition Accuracy Over The Maximumaccuracy Achieved In Individual Representation Scheme Using Fusion Scheme

Rotation in Degree	X-axis FRRI%	Y-axis FRRI %	Z-axis FRRI %
+5,-5	1.10	1.08	1.00
+10,-10	1.24	1.66	1.05
+15,-15	1.31	2.05	1.12
+20,-20	1.31	2.36	1.25
+25,-25	1.29	1.77	1.27

The highest rate of improvement using multiple/fusion spectral representation is almost double the existing accuracy for rotation in Y axis using individual representation, next higher improvement comes on the X-axis rotation and then on Z axis.

TABLE VII : Improvement In Recognition Accuracy 'N-Times' Over The Accuracy Achieved Without Spectral Transformation

Rotation in Degree	X-axis FRRI N-times	Y-axis FRRI N-times	Z-axis FRRI N-times
+5,-5	1.74	1.59	1.08
+10,-10	4.02	4.23	1.13

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+15,-15	10.92	6.92	1.43
+20,-20	13.13	9.29	1.84
+25,-25	10.89	8.67	2.53

TABLE VIII

Rotation in Degree	X Axis Pose Variation				
	Fusion FRR%	R1 FRR%	R2 FRR%	R3 FRR%	R4 FRR%
+5,-5	95.50	55.00	86.50	65.50	85.50
+10,-10	82.50	20.50	66.50	15.50	36.00
+15,-15	65.50	6.00	50.00	6.00	10.50
+20,-20	52.50	4.00	40.00	5.50	3.50
+25,-25	49.00	4.50	38.00	5.00	4.50
Rotation in Degree	**Y Axis Pose Variation**				
	Fusion FRR%	**R1 FRR%**	**R2 FRR%**	**R3 FRR%**	**R4 FRR%**
+5,-5	98.00	61.50	79.00	71.50	90.50
+10,-10	93.00	22.00	56.00	23.50	53.50
+15,-15	83.00	12.00	40.50	10.00	29.00
+20,-20	65.00	7.00	27.50	3.50	5.50
+25,-25	40.00	4.50	22.00	6.50	6.00
Rotation in Degree	**Z Axis Pose Variation**				
	Fusion FRR%	**R1 FRR%**	**R2 FRR%**	**R3 FRR%**	**R4 FRR%**
+5,-5	99.50	92.00	99.50	93.50	94.00
+10,-10	99.00	87.50	94.00	92.50	79.50
+15,-15	98.50	69.00	88.00	80.50	50.50
+20,-20	97.50	53.00	78.00	61.00	29.00
+25,-25	95.00	37.50	75.00	45.00	26.50

Where
R1-With 2D depth data using 2D-PCA,
R2-With 1D-PCA on Euclidean Metric,
R3-With 2D-PCA on DCT of Depth map,
R4-With 2D-PCA on DFT of Depth map
FRR-Face Recognition Rate

An average an improvement (FRRI-Face Recognition Rate Improvement) of 8.14, 6.14 and 1.60 times in accuracy along for X, Y and Z axis respectively is obtained when the depth data is used without pose correction along with multiple spectral representations and Euclidean metric spectral representation as input to PCA to get the weight vectors. These rates are shown in Table VII. The improvement is tabulated by comparing the FRR obtained when testing done using a spatial domain data.

When tested over 1000 samples on each axis of rotation, an accuracy of 97% for Z axis, 75% for Y axis and 68% for X axis is obtained. This result is comparable with existing systems using pose correction. Table VII comparison shows the relative improvement in recognition. Graphical representation of the table is also shown below in Fig.9, Fig.10 and Fig.11. The X axis of graph being the pose angle and Y axis the Face Recognition Rate (FRR) accuracy.

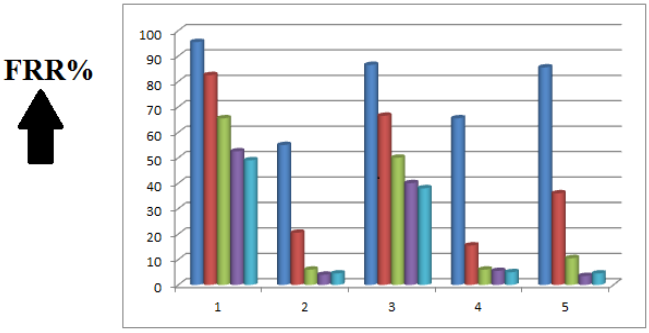

Fig 9: Accuracy Comparison for X axis Pose Variation

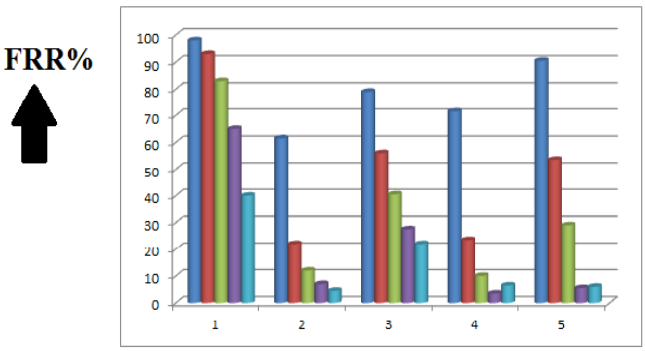

Fig 10: Accuracy Comparison for Y axis Pose Variation

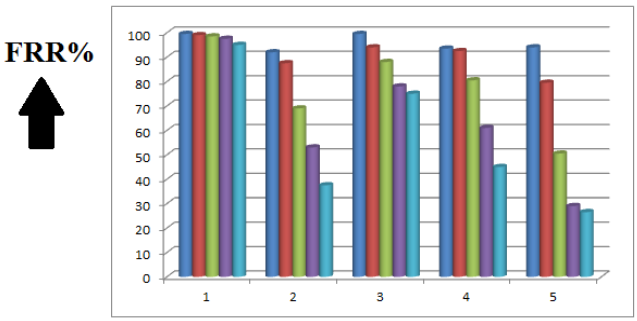

Fig 11: Accuracy Comparison for Z axis Pose Variation

D. Computation time

Testing of algorithm is done on 3GHz, Core I-5 processor; the average testing time for 3000 samples is 766.86 seconds. That is 255ms for testing and validating a single user. This will again increase as the number of subjects increase. By using down sampling and abstracting the data representations computational time can be further reduced. But with a dedicated system, the testing time can be further reduced to microseconds.

IV. CONCLUSION

The fusion algorithm is tested on unregistered 3D Faces with orientations starting from 10 º to 50 º. The algorithm gives an accuracy of 97% for pose variations along Z axis, 75% along Y axis and 68% along X axis.

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Experiments are conducted on various representation types and feature extraction methods for 3D Face recognition. The experimental results show that the features can be effectively extracted from depth data and point cloud using spectral transformation like DFT and DCT. Fusion experiments were conducted at score level. The surface representation of 3D Face data in terms of Euclidean metric with its spectral transformation, in addition to the spectral representation of projected depth information to the XY plane using DFT and DCT are also used. There is ample scope for further improvement using more fusion schemes at the representation level and at spectral level. This method can be implemented in real time systems since the processing time required is lesser on a dedicated system. Dimensional reduction method can also improve the time performance of the system. Advancement of technology in 3D Face capturing and faster processing systems can make the system more efficient in all aspects.

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