Multimodal Approach for Face Recognition using 3D-2D Face Feature 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 for feature extraction significantly increases the operational speed of the system with huge database enrollment. 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. The use of depth information alone in different spectral representation was not sufficient to increase the recognition rate. So a fusion of texture and depth information of face is proposed. 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.

Keywords: Point Cloud, Rotation Invariance, Pose Correction, Depth Map, Spectral Transformations, Texture Map and Principal Component Analysis.

1. 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. Use of texture information along with the geometrical information of the face seems to improve the recognition accuracy of face recognition system when pose correction is not done as a preprocessing step.

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. 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. Hua Gao, Hazım Kemal Ekenel, and Rainer Stiefelhagen[9] used Active Appearance model for fitting faces with pose variations. Mohammad Naser, Moghaddasi Yashar Taghizadegan and 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. Wang et al.,[14] described point signatures in a 3D domain and facial feature points by using Gabor filter responses in a 2D image. Chang *et al.*, [15] tested the recognition algorithm using fusion of 3D and 2D information and was found effective in improving face recognition rate(FRR). C. McCool *et al.*, [16] used Log-Gabor Templates of depth and texture data was used along with Mahalanobis Cosine metric as the distance measure and in [17] PCA difference vectors are modeled using Gaussian Mixture Models (GMMs) and is compared with Mahalanobis Cosine metric. Pamplona Segundo *et al.*, [18] used boosted cascade classifiers using range images as input for scale invariant face detection for the automation of face recognition systems. Jahanbin S *et al.*, [19] 2-D and 3-D Gabor coefficients and the anthropometric distances are calculated and three parallel classifiers are fused at the match score level to form a face recognition system.

A typical 3D Face is shown in Figure.1. Figure.2 represents its axis level representation. Figure 3 and 4 represents the texture map with two different orientations.

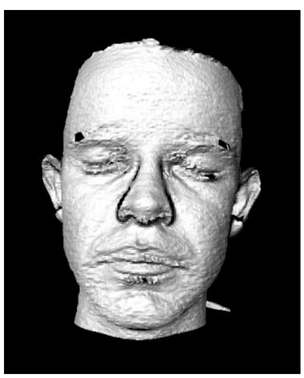

FIGURE 1: 3D Face Model.

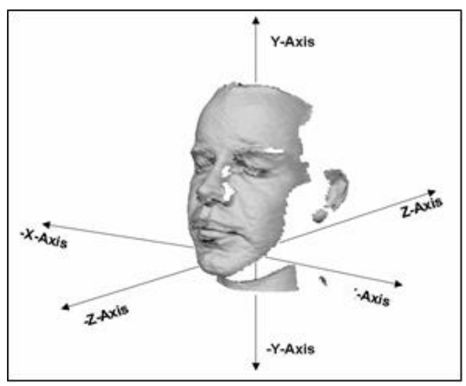

FIGURE 2: 3D Face in Space.

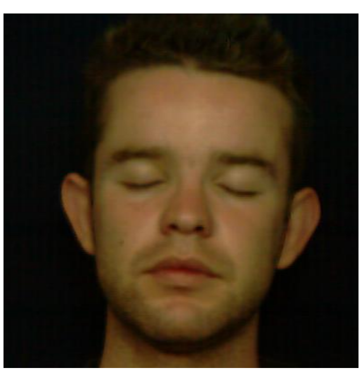

FIGURE 3: 2D Texture Map (Frontal View).

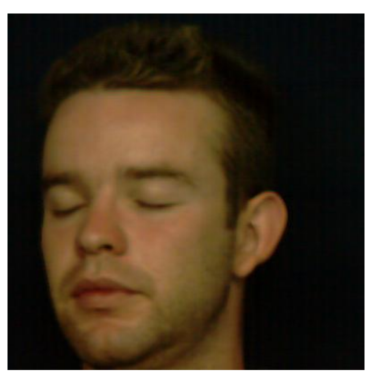

FIGURE 4: 2D Texture Map (Left Turned Head).

First the fusion 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 generated from same raw data. 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. Use of Depth information alone is not sufficient for an efficient recognition system since pose correction is not done. So texture information is also incorporated with the fusion scheme.

2. PROPOSED IDEA FOR FACE RECOGNITION

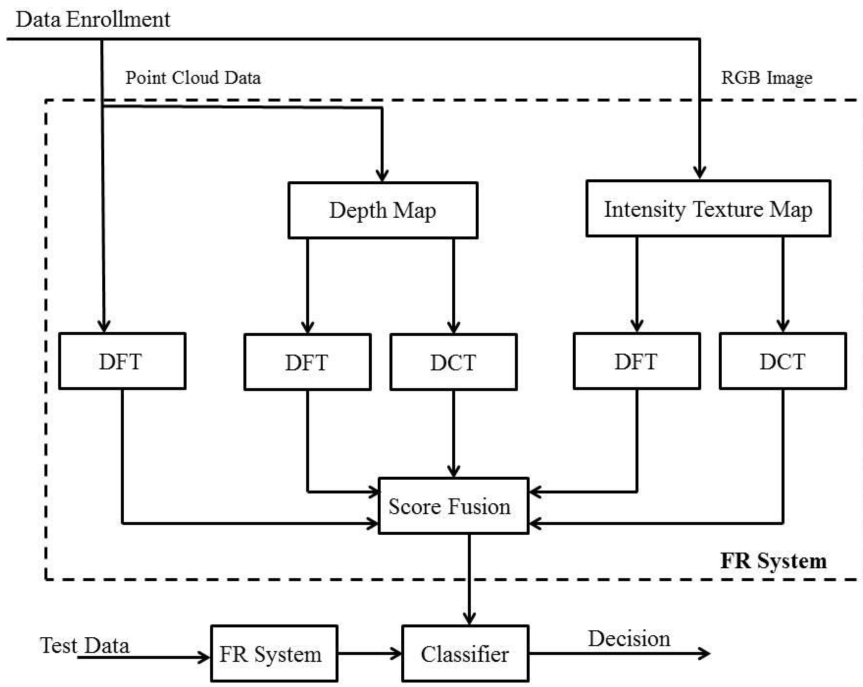

FIGURE 5: Proposed Method **.**

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 and 2D-DFT along with 2D-DCT. These spectral transformations transform the data to a better representation which increases the accuracy of recognition system.

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 or in any complex plane.

The 3D Face recognition scheme is affected by pose variations of the subject (person under consideration). 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 and Z 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.

Here FRAV3D database is considered. It contains the facial data with different face orientations and expressions. When depth information alone was considered the Face recognition accuracy (FRA) was not high. So texture data of face is also considered which significantly improves the FRA.

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. Texture information is available as RGB image of size 400x400. This image is converted to intensity image and is down sampled by a factor 2 to reduce the computation time. Down sampling doesn't reduce the FRA, it is verified.

The proposed method involves the following steps given below in sequence. As a preliminary step Z component of the point cloud data alone is taken and DFT is applied on this data to get 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 (Figure 7 and Figure 8). On this ROI data 2D-DFT and 2D-DCT is applied. Simultaneously spectral representation of Texture map is also taken using 2D-DCT and 2D-DFT. 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. Here 2D PCA is used for depth and texture features and 1D PCA for Z component of point Cloud.

2.1 Point Cloud Representation as a One Dimensional Vector

We have the point cloud data as an M x 3 matrix. Of this the third dimension, which is the depth information alone is taken. This reduces the number of points under consideration to M while the original being 3M. This also aids the real time implementation of the system faster. We call this data as Metric.

The Metric data will be distributed in spatial domain as shown in Figure 6. It relate to the data of Z axis with some unknown orientation and scale. 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. Transformation of Metric data to spectral domain can be done using 1D-DFT, using equation (2).

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

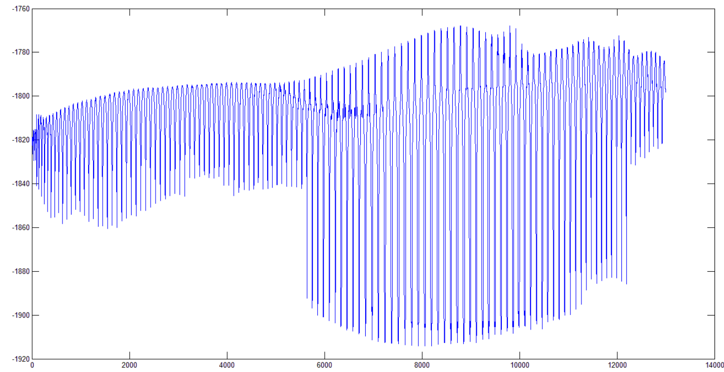

FIGURE 6: Metric in Spatial Domain.

2.2 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 Figure 7 and Figure 8. Figure 9 represents the depth map obtained from point cloud data oriented in different axis.

FIGURE 7: Depth Map.

FIGURE 8: ROI from Depth Map.

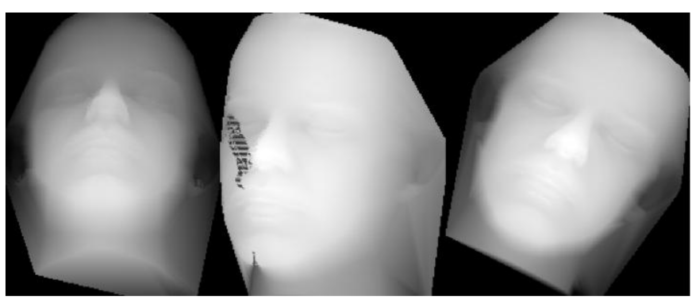

FIGURE 9: Depth Map with different pose variations along X, Y and Z axis.

2.3 Use of 2D DFT and 2D DCT on Depth Data and Texture Map

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 magnitude of 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 Figure 10. Here the global feature extraction by DCT is made used of. DCT has the property of de-correlation which enables the data structure to loose 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 Figure.10.

$$F(u,v)=\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\cos\left(\frac{(2x+1)\pi u}{2M}\right)\cos\left(\frac{(2y+1)\pi v}{2N}\right) \text{, for a M x N depth image.} \quad (3)$$

Again the depth image is transformed using 2D-DFT so that rotation effects are reduced. DFT is a rotation invariant transformation. So that the distributed pixel values (normalized) are properly aligned, this enables the pattern matching more efficient. DFT spectrum of face image will appear as shown in Figure 11. Transformation to spectral domain using 2D Discrete Fourier Transformation can be done using equation (4).

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

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

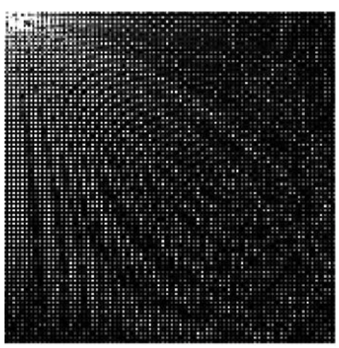

FIGURE 10: DCT Representation of ROI Depth Map. **FIGURE 11:** DFT Representation of ROI Depth Map.

The same procedure is repeated for the texture map also to get the spectral representation of gray scale intensity image using 2D-DCT as shown in Figure 12 and using 2D-DFT as in Figure 13.

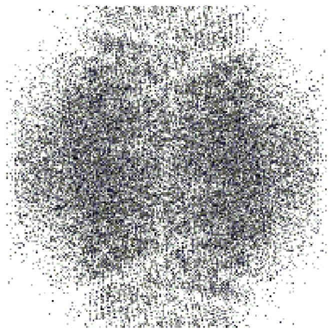

FIGURE 12: DFT Representation of Texture Map.

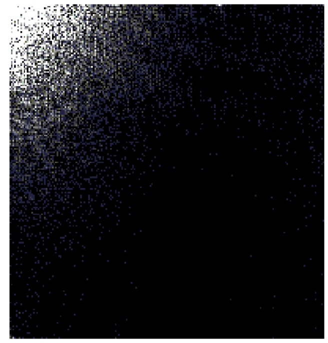

FIGURE 13: DCT Representation of Texture Map.

2.4 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 X_i be the spectral transformed 1D Euclidean Metric which representations 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

$$X_m = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{5}$$

Standard deviation will be calculated

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

Covariance matrix is calculated

$$X_{COV} = X_{SD*}\, X^T{}_{SD} \tag{7}$$

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.

$$X_{COV} = X^T{}_{SD*}\, X_{SD} \tag{8}$$

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-PCA 2D 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.

2.5 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 equation9.

$$W= [W\_DMDCT\ W\_DMDFT\ W\_PCDFT\ W\_TMDCT\ W\_TMDFT] \tag{9}$$

$$E= [Error\_DMDCT\ Error\_DMDFT\ Error\_PCDFT\ Error\_TMDCT\ Error\_TMDFT] \tag{10}$$

$$Error= W*E^T \tag{11}$$

On the equation 11 W_DMDCT is weight for error value obtained using 2D DCT on depth data and is its value is taken as 1 , W_DMDFT and W_PCDFT are weights for the error value obtained using 2D DFT and 1D DFT on depth map and 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. Similarly texture score weights W_TMDCT, W_TMDFT are the weights of error score obtained using 2D DCT and 2D-DFT on intensity image. Weight value can be approximated using equation 12, 13, 14 and 15.

$$\frac{1}{W\_DMDFT} = \frac{Error\_DFT}{Error\_DCT}\text{, rounded to } 10^2\text{'s.} \tag{12}$$

$$\frac{1}{W\_PCDFT} = \frac{Error\_PCDFT}{Error\_DCT}\text{, rounded to } 10^9\text{'s.} \tag{13}$$

$$\frac{1}{W\_TMDCT} = \frac{Error\_TMDCT}{Error\_DCT} \approx 1 \tag{14}$$

$$\frac{1}{W\_TMDFT} = \frac{Error\_TMDFT}{Error\_DCT}\text{, rounded to } 10^2\text{'s} \tag{15}$$

These values give optimum recognition accuracy. Finding an optimum weight for this error function which can minimize it can be another optimization problem.

3. RESULTS

3.1 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 pose and orientations as Frontal, Right turn 25º (respect to Y axis), Left turn 5º (respect to Y axis), Severe right turn (respect to Z axis), Soft left turn (respect to Z axis), Smiling face, Open mouth, Looking upwards (turn respect to X axis), Looking downwards (turn respect to X axis), Frontal view with lighting changes etc. A substantial change in the recognition accuracy is observed with fusion scheme.

First recognition accuracy obtained with Depth data and Point cloud metric will be considered. Accuracy is checked by varying the number of faces from 10 to 100, with enrollment increment of

2 faces and a summary is shown in Table 1. When the DCT of Depth Map is analyzed the accuracy variance is about 9.12% with maximum of 54.44% and minimum of 45%, for DFT it is 14.40% with maximum of 57.29 % and minimum of 46.67% and for Point Cloud metric it is 17.13 % with maximum of 60 % and minimum of 43.33%.

No of Subjects	Total Face Samples Tested	Depth Map DCT	Depth Map DFT	Metric DFT
		Accuracy	Accuracy	Accuracy
60	960	48.33	48.33	43.33
90	1440	54.44	56.67	45.56
100	1600	53.00	56.00	46.00

TABLE 1: Comparison of Accuracy obtained using Depth Map Spectral Transformation and Point Cloud Metric.

When the reliability of a Face recognition system is considered, the system should correctly classify the users based on the current pose and posture of the user. A user can be enrolled in the data base of the FR system mostly in limited number of pose/ expression variations. As the number of enrollment sessions increases the system will be trained in such a way that the user can be correctly identified in a latter testing session. But it does have a limitation unless the training sessions given are sufficient which covers all the pose, translation and expression variations.

Here such an analysis is done to check the reliability of the system. The summary results are shown in Table 2.

When Table 2 is analyzed, it can be observed that all 16 sessions are not identified by any of the feature extraction scheme. For example, 7 sessions are successfully identified only by 39 enrolled faces when DCT is used, 46 when DFT is used and 43 when point cloud metric is used out of the total 100 enrolled faces. Obviously this brings down the overall recognition accuracy of the system and hence the reliability. In other words only 273, 322 and 301 samples out of 1600 samples were successfully identified while others are rejected.

	Depth Map DCT	Depth Map DFT	Point Cloud DFT
Sessions	Subjects	Subjects	Subjects
1	100	100	100
2	96	96	96
3	87	91	85
4	82	81	69
5	69	73	55
6	53	61	49
7	39	46	43
8	28	30	33
9	19	22	24
10	14	13	14
11	7	3	10
12	4	1	5
13	2	1	1
14	0	1	1
15	0	0	0
16	0	0	0

TABLE 2: Comparison of number of enrolled faces successfully identified in 16 different sessions.

3.2 Results of Fusion Scheme Analysis

As explained earlier, when Texture Map Score obtained by the spectral transformation of RGB data using 2D-DCT and 2D-DFT is also fused with the score obtained using depth data notable improvement in recognition accuracy is observed. Those observations are shown in Table 3. It can be also noted that the accuracy deviation with final fusion scheme is nearly 4.17%, i.e. the system is reliable even when more number of faces are enrolled and face recognition accuracy won't drop too much.

No of Subjects	Total Face Samples Tested	Fusion DM	FUSION of DM and TM
		Accuracy	Accuracy
60	960	50.31	74.58
90	1440	52.36	76.88
100	1600	52.44	78

TABLE 3: Comparison of FRR of Texture fusion scheme with FRR of Depth Fusion scheme.

When Table 3 is analyzed the accuracy variance for Depth Score Fusion is also around 4.06%. In short fusion of individual score of different representations reduces the accuracy variance and hence increases the reliability of the FR systems.

Table 4 shows the difference in number of subjects identified with fusion of Texture and Depth spectral representation scores and depth alone.

	Fusion DM	**Fusion of DM and TM**
Sessions	Subjects	Subjects
1	100	100
2	100	100
3	99	100
4	97	100
5	92	100
6	83	100
7	80	95
8	67	87
9	61	82
10	50	73
11	41	66
12	30	55
13	20	37
14	13	25
15	5	14
16	1	3

TABLE 4: Comparison of number of enrolled faces successfully identified in each sessions.

All testing are done only with a single image enrolled in data base as the reference Image. When the images in the database itself are fed as the test image the accuracy is 100% itself. All other samples are tested as the class that is not present in the database, which ensures that the accuracy obtained in the proposed system is insensitive to the session variations and least sensitive to pose and expression variations. The insensitivity is very clear from the accuracy obtained using fusion schemes. Even when the number of samples is doubled, say from 800 to 1600, the FRR change is near to 2% only. Testing with 160 samples which contains complex pose variations and expressions gave 80% accuracy and 1600 samples gave an accuracy of 78% which ensure that the system is reliable.

The main reason for the reduction in accuracy is due to the loss of laser signals while scanning the face and the occlusions due to pose variations [13]. The advantage of proposed work is that face alignment or face registration is not done here. The registration process takes sufficient computation time and it is not acceptable in real time systems. This system requires only a single image as training image for achieving this much accuracy. By increasing the number of training images FRR can be further improved. This method seems to perform better when compared to [10] where the recognition rate is only 70% with a single training image. While 2D PCA [11] method gives 76.2% when tested over 540 samples.

3.3 Improvement In Accuracy Rates by Fusion Scheme

When the accuracy obtained in the fusion scheme is analyzed, when depth data is fused with texture information a significant improvement is observed as shown in Table 5.

No of Subjects	Correct samples additionally recognized	Fusion DM and TM
		Improvement in FRR
60	464	48.23
70	507	45.21
90	675	46.83
100	769	48.04

TABLE 5: Improvement in FRR with fusion of Depth and Texture information.

Almost an average improvement of nearly 48% can be obtained when the fusion scheme is used.

3.4 Face Recognition Rate-Graphical Comparison

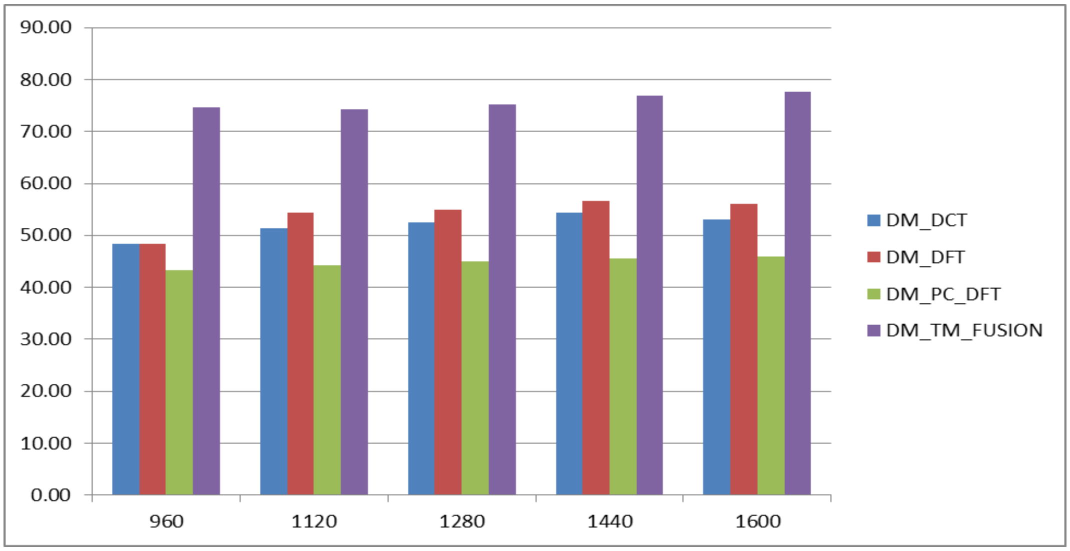

FIGURE 14: FRR Comparison of Individual and Fusion Scheme.

3.5 Computation Time

Testing of algorithm is done on 3GHz, Core I-5 processor; the average identification time per sample is 400ms.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.

4. CONCLUSIONS

The fusion algorithm is tested on unregistered 3D Faces with different pose orientations and expressions. The algorithm gives an accuracy of 78% even with unregistered face data. 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, point cloud and texture map using spectral transformation like DFT and DCT. Fusion experiments were conducted at score level. The surface representation of 3D Face data in terms of metric with its spectral transformation, in addition to the spectral representation of projected depth information to the XY plane and Intensity image as texture Map using 2D-DFT and 2D-DCT are also used. When the numbers of subjects in the database are increased, the recognition rate remained more or less same which shows that the further enrollment of faces in the database won't affect the true recognition rate. 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.

Acknowledgment
Thanks are due to Dr. Enrique Cabello, Universidad Rey Juan Carlos, Spain, for providing us with the FRAV3D database.

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