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REVIEW ON MULTIMODAL FACE RECOGNITION SYSTEM USING SPECTRAL TRANSFORMATION OF 2D TEXTURE FEATURE AND STATISTICAL PROCESSING OF FACE RANGE IMAGES

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Abstract: For as far back as couple of decades in design acknowledgment 3D Face acknowledgment has been a range of intrigue. As the requirement for client recognizable proof/validation has expanded significantly amid late years, there is a reestablished enthusiasm for enhancing face acknowledgment precision rates to levels accomplished by other. This paper concentrates on issues of individual distinguishing proof utilizing 3D Face information. Here unregistered Face information, i.e. both surface and profundity is sustained to classifier in ghostly portrayals of information. 2D Discrete Fourier Transform (DFT) is utilized for otherworldly portrayal. more prominent biometrics Fusion of scores enhances the acknowledgment precision altogether since utilization of profundity data alone in ghastly portrayal was not adequate to build exactness. Measurable technique appears to corrupt execution of framework when connected to surface information and was successful for profundity information. The geometry of face as 2D pictures and apply the ordinary 2D confront acknowledgment calculations in such frameworks.
Keywords –Point Cloud, Rotation Invariance, Pose Correction, Depth Map, Spectral Transformations, CDF, Texture Map and Principal Component Analysis.

1. INTRODUCTION

3D Face recognition has been a dynamic area of research in the past spans. The problems come across in the enrollment phase and the huge computational requirements in the implementation phase have been the major burden in this area of research. The situation has improved enormously due to the latest inventions in 3D imaging devices and has made 3D Face recognition system a dependable choice in security systems based on Biometrics.Though poor resolution is, a foremostdisadvantagemet in 3D Face images the geometricaldata 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, effort 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 data other than the 3D facial scan. The system arrives at an identity from among the registered faces in the record. Use of texture data along with the geometrical data of the face seems to progress the recognition accuracy of face recognition system when pose correction is not done as a pre-processing step. Here statistical processing of depth data used to improve the recognition precision.

2Alexander M. Bronstein et al. proposed an idea of face recognition using geometric invariants using Geodesic distances. 3C. Beumier utilized parallel planar cuts of the facial surfaces for comparison. 4Gang Pan et al extracted ROI of facial surface by considering bilateral symmetry of facial plane. 5Xue Yuan et al proposed a face recognition system using PCA, Fuzzy clustering and Parallel Neural networks.

A typical 3D Face is shown in Fig. 1. Fig. 2 denotes its axis level representation. Fig. 3 and 4 denotes the texture map with two diverse orientations.

Fig 1:3D Face Model

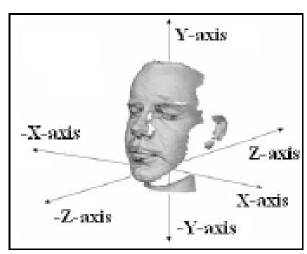

Fig 2:3D Face in Space

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Fig 3:2D Texture Map(Frontal View)

Fig 4:2D Texture Map(Left Turned Head)

Since only a thin set of points are accessible in the dataset, it is essential to upsurge the data density by using many data representations produced from same raw data. For this the data is converted into spectral domain using DFT. This sparse set of data with obstruction 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 combined with the fusion scheme.

2. EXISTING METHODS FOR FACE RECOGNITION

The framework goes for extracting the component from the info information through element extraction devices and wires the scores to show sign of improvement acknowledgement precision. The primary component extraction rule utilized as a part of this framework is the unearthly change. The phantom change apparatus utilized here is 2D-Discrete Fourier Transform. These ghastly changes change the information to a superior portrayal, which expands the exactness of acknowledgement framework.

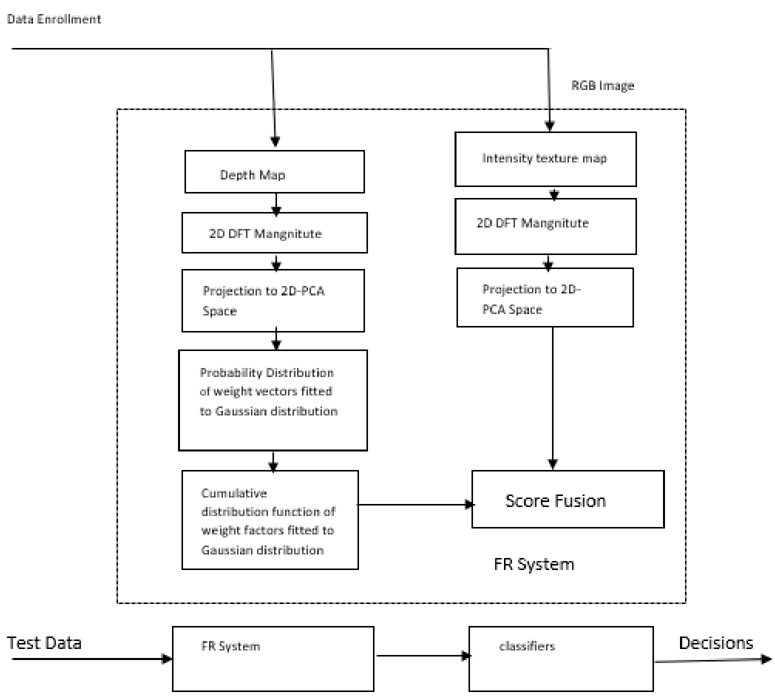

Fig 5: Method for Face Recogination

The most vital piece of this work lies in the example characterization issue. An example of information focuses is accessible. This example is not adequate for the acknowledgement framework to work since the information will be exceedingly blocked because of posture varieties in the X, Y and Z pivot or in any perplexing plane.The 3D Face acknowledgement conspire is influenced by posture varieties of the subject (individual under thought). There are techniques accessible in which the remedy to this impact of posture varieties likewise is incorporated. One such strategy is the iterative closest point(ICP) calculation. In any case, the fundamental burden of these strategies is that a reference confront is to be utilized as a model for other pivoted countenances to be rectified. Additionally the handling time taken is high. Further, the dependability of this outcome relies upon the precision in determination of the reference confront display utilized. Thusly, in this work done this remedy to the impact of stance variety isnot considered. The strategy goes for perceiving the subject without much computionally complex numerical method. Additionally the outcomes demonstrate that the effectiveness of ramework is practically identical with a framework with posture adjustment. The thought behind unearthly portrayal of information is that, when information is in partial area, examination will be done as coordinated pixel level or voxel level. Therefore, the urn and interpretation of information will profoundly influence the outcome. In addition, the precision of the framework will go down to even 5% under serious stance varieties in X, Y and Z hub. At the point, when unearthly change is done the conveyed information will be concentrated or it might be spoken to in a uniform manner.

Here FRAV3D database is considered. It contains the facial information with various face introductions and demeanors. At the point when profundity data alone was viewed as the face acknowledgement precision (FRA) was not high. So surface information of face is likewise considered which essentially enhances theFRA. The information accessible for the examination and testing will be in Depth Map design which is a framework exhibit of size M x N. for each face profundity information input the quantity of profundity focuses in 2D plane can be extraordinary.

The method involves the following steps given below in sequence.

1) The 2D face depth data is first normalized with the maximum intensity value. 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.6 and Fig.7).

2) On this ROI data, 2D-DFT is applied. The detailed explanations are given on following sections. Simultaneously 2D-DFT is applied over the complete face texture data.

3) Once spectral representations are obtained, Principal Component Analysis (PCA) is applied on that data to get the corresponding weight vectors.

4) Now probability distribution of the weight vectors of depth data is computed by fitting it onto Gaussian distribution. After this fitting process, corresponding CDF is calculated as a new feature vector called Cumulative Depth Feature Vector (CDFV).

5) CDFV along with weight vector of texture data is fed to classifier, which uses Euclidean distance for classification. Individual error scores are calculated and then these scores are fused to get the minimum score.

2.1 Depth Map Normalization

Depth map establish is normalized with the supreme intensity value to create the depth data more noticeable. Here the depth values are normalized between the range 0 and 255.

$$\text{Normalized Depthmap} = \frac{\text{Original Depthman} *255}{\text{MaxIntenity (Original Depthman)}} \quad (1)$$

2.2 Nose tip Localization and face area extraction

For limiting the nose tip, most extreme force strategy is utilized. In this technique presumption is influenced that the nose to tip will be he point with greatest pixel power. Once the nose tip is discovered the roundabout region (ROI) around the nose tip is separated utilizing an ideal sweep of 55. Presently the profundity guide will contain the face zone just, all other undesirable segments are trimmed away. Next face region is bought together by influencing the bose to tip as the middle pixel of he picture. Generally the coordinating procedure will bring about a lower exactness. The face range is likewise standardized by the most extreme power. The centralized face image is as shown in Fig. 6 and Fig. 7.

Fig 6:Depth Map

Fig 7: ROI from Depth Map

2.3 2D Discrete Fourier Transform

The profundity information will have the pixel esteem as the geometrical measure of the facial information. Face picture have higher repetition. Here just the greatness of otherworldly information is taken alone since it is not changed back to spatial area in any of the preparing stages.

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 depth image will appear as shoen in Fig. 8. Transformation to spectral domain using 2D Discrete Fourier Transformation can be done using equation.

$$F(U,V) = \sum_{y=0}^{M=1} \sum_{y=0}^{N=1} f(x,y) e^{-j2\pi(\frac{Ux}{M}+\frac{Vy}{N})}, \text{for a M x N depth image} \quad (2)$$

Fig 8: DFT Representation Of ROI Depth Map

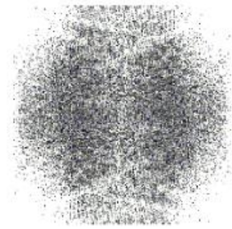

Fig9: DFT Representation Of Texture Map

The same procedure is repeated for the texture map having a resolution of 400 x 400, also to get the spectral represtantion of gray scale intensity image using 2D-DFT as in Fig. 9.

2.4 Principal Component analysis

Use of spectral changes will make the data samples almost spatially uncorrelated. Even then, some spatial dependence may exist. So Principal Component Analysis (PCA), which uses the orthogonal changes to get linear uncorrelated data sets called Principal Components, is employed. Conventional covariance method is used for the above. To start with, feature withdrawal using 1D-PCA is discussed for better understanding. Let Xi be the spectral transformed 1D data which representations ith person, it is grouped as a M' x N matrix X=[X1 X2 …XN], where N is the number of face samples under consideration and M' is the length of each feature vector.

Mean vector is calculated as follows:

$$X_m = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (3)$$

Standard Deviation is calculated as follows:

$$X_{SD} = \frac{1}{N}\sum_{i=1}^{N}(x_i - x_m) \quad (4)$$

Covariance matrix is calculated as :

$$X_{cov} = X_{SD} + X_{SD}^{T} \quad (5)$$

Here, the covariance matrix is of size M' x M', which is of very huge dimension. Also it gives M' Eigen values and M' Eigen vectors which are too large in number to process. Therefore, dimensional decrease is adopted by altering the building of covariance matrix as follows.

$$\mu = \frac{1}{M}\sum_{i=1}^{M} Wi \quad (6)$$

$$\sigma = \frac{1}{M}\sum_{i=1}^{M}(Wi - \mu) \quad (7)$$

The product is a matrix having dimension 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 the first N' largest Eigen values and matching Eigen vectors are selected, as others are irrelevant. Eigen vectors in N' dimension is transformed to the higher dimension of M' by multiplying with Standard deviation Matrix. The test data is projected to this lower dimension space to get the corresponding weight vectors. Now feature extraction using 2D-PCA is considered using spectral representation of depth map. The only difference with 1D-PCA in calculating the Covariance matrix is that here a 2D matrix is used when compared to 1D Matrix in 1D-PCA. After decisive the Eigen values and Eigen vectors, a 2D weight vector matrix is obtained which is then transformed to a column matrix.

2.5 Cumulative Depth Feature Vector

Projection of depth data Fourier transform spectral numbers on 2D PCA space will give weight vectors. These weight vectors are fitted on to the chance distribution function of a Gaussian distribution. The mean and standard deviation of the Gaussian distribution is calculated as follows. If Wi is the weight vector,There are dissimilar probability distributions and of which some can be fitted more closely to the witnessed frequency of the data than others. Difference distributions were fitted as test onto the depth weight vector and the Gaussian distribution seemed to be more effective when the data distribution is concerned.

$$F(x,\mu,\sigma)=\frac{1}{\sqrt{2\pi\sigma^2}}\,e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \tag{8}$$

$$F(x)=\sum_{xi\leq x} f(X=xi) \tag{9}$$

2.6 Score Fusion

Next, the error score is projected using all the multiple representations distinctly. For processing 2D DFT representation, 2D-PCA is used. 1D-PCA was also experimented for the 2D representations but 2D-PCA gave better result for 2D representations. Fault values are calculated for each data representations and all this error values are joint as a single error value using the linear expression as given in equation 10.

$$\text{Error} = W*\text{Texture\_Error\_DFT\_Norm}+(1-W)*\text{Depth\_Error\_DFT\_Norm} \tag{10}$$

$$\text{Texture\_Error\_DFT\_Norm} = \text{Texture\_ErrorDFT} - \frac{\min(\text{Texture\_ErrorDFT})}{\max(\text{Texture\_ErrorDFT})-\min(\text{Texture\_ErrorDFT})x} \tag{11}$$

$$\text{Depth\_Error\_DFT\_Norm}=\text{Depth\_ErrorDFT}-\frac{\min(\text{Depth\_ErrorDFT})}{\max(\text{Depth\_ErrorDFT})-\min(\text{Depth\_ErrorDFT})} \tag{12}$$

By trial and error,the optimum value for W can be approximately obtained in the range -1 and +1

3. CONCLUSION

The combination calculation is tried on unregistered 2D Faces with introductions along X, Y and Z hub with outward appearances. The calculation gives a most extreme precision of 90%, when tried together more than 1300 specimens. The exploratory outcomes demonstrate that the highlights can be adequately removed from 2D profundity information utilizing factual portrayal of phantom data and surface information utilizing unearthly change. Here combination tests were directed at score level. There is adequate extension for assist change utilizing more combination plans at the portrayal level and at ghostly level. The technique can likewise be actualized continuously frameworks since the handling time required is less.

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