3-D Face Recognition Using Improved 3D Mixed Transform

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Abstract

This paper deals with the using of Improved 3D Mixed Transform (3D-IMT) for face recognition problem. The mixed transform consists Fourier based 3D radon transform plus 1-D Wavelet transform (which is also known as 3D Ridgelet transform). The Mixed Transform is improved by using the Particle swarm optimization (PSO) technique. The improvement involves the selection of the best of directions for smart rectangle-to-polar transform as a part of the 3D Radon Transformation. The 3D-IMT is applied to the 3D representation of face images, and yields a few number of features, these features is projected into the maximized projection that achieves good recognition rate using the Linear Discriminant Analysis (LDA).

Keywords: Face Recognition, 3-D Radon Transform, Particle Swarm Optimization (PSO), Wavelet Transform ,Linear Discriminate Analysis (LDA) .

1. INTRODUCTION

1.1. Face Recognition Problem

Face recognition is one of the most important biometrics which seems to be a good compromise between actuality and social reception and balances security and privacy well. It has a variety of potential applications in information security law enforcement, access controls. Face recognition systems fall into two categories: verification and identification, Face verification is 1:1 match that compares a face images against a template face image. On the other hand face identification is 1:N problem that compares a probe face image against all image templates in a face database. Face recognition is a very difficult problem due to a substantial variation in light direction (illumination) , different face poses , and diversified facial expressions, Aging (changing the face over time), Occlusions (like glasses, hair, cosmetics) , so building an automated system that accomplishes such objectives is very challenging. In last decade many systems with recognition rate greater than 90% has been done. However a perfect system with 100% recognition rate remains a challenge. Face recognition algorithms are divided by [1,2] into three categories, as follows:-

1. Holistic methods: These methods identify a face using the whole face images as input and extract the overall features.
2. Feature based methods: these methods used the local facial features for recognition (like eyes , mouths, fiducial points ..etc.)

3. Hybrid methods: these methods used both feature based and holistic features to recognize a face. These methods have the potential to offer better performance than individuals.

1.2. Three Dimensional (3D) Face Recognition

The vast majority of Researches deal with methods based on 2D image processing using intensity or color images which reached higher than 90% recognition rate under controlled lighting conditions whoever the performances drop in case of pose, illumination and expression variation. Almost the 2D techniques still encounters many difficulties. On the other hand the three dimensional (3D) face recognition technologies is now emerging, in part, due to the availability of improved 3D imaging devices and processing algorithms. The main argument in favor of using 3D information for face recognition appears to be that it allows us to exploit feature based on shape and the curvature of the face without being plagued by the variances caused by lighting also the pose variation can be corrected by rigid rotations in 3D space they also provide structural information about the face (e.g., surface curvature and geodesic distances) which cannot be obtained from a single 2D image. The 3D face recognition algorithms can be broadly classified into three groups [3], first, there are the 3D appearance based techniques these techniques include the statistical methods like PCA and 3D PCA, ICA, LDA, 3D techniques based on ICA and LDA have been reported to perform better than 3D PCA. The second class use a 3D facial surfaces to represents individuals these 3D models are rotated and translated using Iterative Closest Point (ICP) algorithm the ICP based algorithms are reported to be robust to variable facial poses and illumination the expression variation can be deal with using intrinsic representation of facial surfaces. The third class is the local feature based 3D face recognition techniques that employ structural properties of local regions of the 3D face. Some of techniques in this class employ facial profiles for matching 3D faces it is reported that the central vertical facial profile has been noted to be effective at uniquely identifying individuals. Other using local geometric characteristics of facial sub regions including their positional coordinates, surface areas and curvatures , and the 3D Euclidean distances, ratios of distances, joint differential invariants, and angles between the local facial regions. A few attempts have been made to automatically locate facial landmarks on 3D models using surface. A number of techniques based on local facial features have been reported to perform better than 3D PCA and ICP [4].

1.3. Three Dimensional (3D) Image Representation Techniques

Two main representations are commonly used to model faces in 3D space [5]. These are the Point clouds or triangulated surface meshes and Range Images (also referred to as a 2.5D surface or depth map). The point cloud representation contains the (x, y, z) coordinates of a set of points on the facial surface. A range image consists of (x, y) points on a regular rectangular grid each (x, y) point is associated with a z value of the point on the surface closest to the acquisition device. The Techniques which are currently being used to obtain 3D information include [6]:-

- Scanning systems: using Laser face scanner.
- Structured light systems: These systems make use of the principles of stereo vision to obtain the range data.
- Stereo vision systems: These systems that attempt to extract 3D information from two or more 2D images taken from different angles.
- Reverse rendering/shape from shading.

1.4. A Brief Historical Review of 3D Faces Recognition

Many surveys has been published [6,7,8] about the 3D Face Recognition most papers report performance as rank-one recognition rate although some report equal-error rate or verification rate at a specified false accept rate but on a limited number of persons and only a few have dealt with data sets that explicitly incorporate pose and/or expression variation.
Cartox et al. [9]approached 3D face recognition by segmenting a range image based on principal curvature they reported 100% recognition rate for either in small data set (5 persons and database size was 18 images).

Nagamine et al.[10] approach 3D face recognition by finding five feature points, using those points to standardize face pose.

Experiments are performed for 16 subjects with 10 images per subject the reported performance was 100% but the computational requirements were apparently regarded as severe.
Hesher et al. [11] explore PCA style approaches the image data set has six different facial expressions for each 37 subjects the reported performance is 97%.
Lu et al.[12] , using ICP-based approach performed on point set Images the approach assumes that the gallery 3D image is a more complete face model and the probe image is a frontal view that likely a subset of gallery image. In experiment with 18 persons a recognition rate of 96% was reported.

Russ et al.[13] presented results of Hausdorff matching on range images they used portions of FRGC v1 dataset they reported 98% as a probability of correct verification.

Chang et al. [14] describe a "multi-region" approach to 3D face recognition. It is a type of classifier ensemble approach in which multiple overlapping sub regions around the nose are independently matched using ICP and the results of the 3D matched are fused. The experimental evaluation using the FRGC v2 data set was conducted in which one neutral-expression image is enrolled as the gallery for each person. Performance of 92% rank-one recognition rate was reported.
Passalis et al.[15] described an approach to 3D face recognition that uses annotated deformable models. An average 3D face is computed on a statistical basis from a training set. Landmarks are selected based on descriptions by Frakas. Experimental results are presented using the FRGC v2 data set. For an identification experiment in which one image per person is enrolled in the gallery (466 total) and all later images(3541) are used as a probe, performance reaches nearly 90% rank-one recognition.

Gupta S. et al.[3] they present a novel anthropometric 3D (Anthroface 3D) face recognition algorithm. It is a completely automatic face recognition algorithm that employs facial 3d Euclidean and geodesic distances between 10 automatically located anthropometric facial fiducial points and a linear discriminant classifier. On a database of 1149 facial images of 118 subjects the EER=1.98% and rank one recognition rate of 96.8% was achieved.

Sina Jahanbin et al.[16] They present a novel identity verification system based on Gabor features extracted from range image . Multiple landmarks (fiducials) on face are automatically detected the Gabor features on all fiducials are concatenated to form a feature vector then the LDA is used. The novel features were tested on 1196 range images from Texas 3DFRC database the reported EER was 2.2%.

Hengliang Tang et al.[17] They presented a novel 3D face recognition algorithm based on sparse representation. First, a 3D face normalization deal with the raw faces. Then, three types of facial geometrical features are extracted to describe the 3D faces after that a feature ranking is performed using (FLDA). Finally, the sparse representation framework is used to collect all the face features. The experiments tested on the BJUT-3D and FRGC v2 databases. The reported recognition rate is 95.3% for the method of fusing the three types of features.

2. THE PROPOSED METHOD

Our approach for 3D Face Recognition is depicted in figure (1). The range Images were used from the Texas3DFR Database [38]. Firstly, the images were preprocessed by interpolation method in order to remove the holes due to spikes these Range images are translated into 3D space using topography representation as 3D array these 3D data is transformed into 3D Radon space using 3D Radon Transform (3DRT). The (3DRT) is optimized by Particle Swarm Optimization (PSO) to select the best directions (i.e. θ, □). These directions achieve a high recognition rate as well as the minimum number of features. The selected features in Radon space is translated into two parts using 1-D Wavelet Transform then only one part is selected so only a half number of features are used. These features are projected into maximized discriminate projection using Linear Discriminant Analysis (LDA).

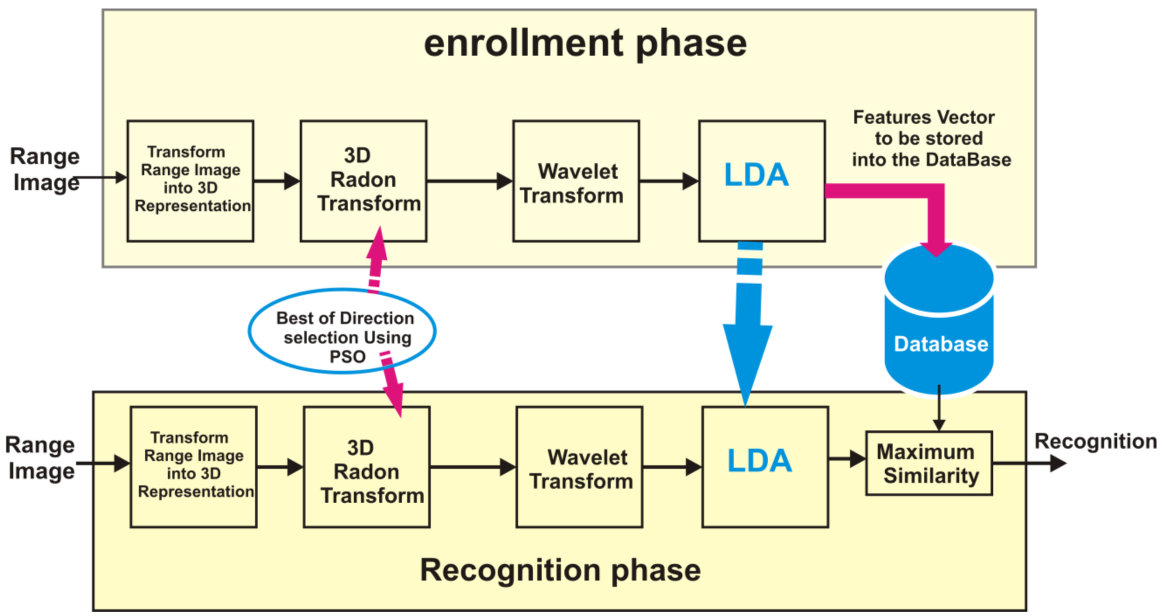

FIGURE 1: The system block diagram.

2.1 The 3D Radon Transform

2.1.1 Introduction

The 3D Radon Transform integrates on planes. Let f(X) be a three dimensional signal where X=[x, y, z]. Let, also ζ be a unit vector in R3 and ρ a real number. The 3D Radon Transform RT(ζ , ρ) of the f(x), is a function which associates to each pair (ζ , ρ) the integral of f(x) on the plane $\Pi(\zeta , \rho)=\{x \mid x . \zeta=\rho \}$ [18] .
The 3D Radon Transform is given by the formula:

$$\mathrm{RT}(\zeta , \rho)=\int_{-\infty}^{+\infty} f(x)\delta(X.\xi - \rho)dx \qquad (1)$$

Since ζ can be written in spherical coordinates as ζ=[cosϕsinθ ,sinϕcosθ,cosθ] then equation (1) can be rewritten:

$$\mathrm{RT}(\rho,\theta,\phi)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y,z)\,.\,\delta(x\cos\phi\sin\theta + y\sin\phi\sin\theta + z\cos\theta - \rho)dxdydz \qquad (2)$$

Each value of the RT(ρ,θ,ϕ) expresses the summation of the values of f(x,y,z) which lie on the plane defined by the parameters (ρ,θ,ϕ).

2.1.2 Radon Transform Using Fast Fourier Transform

A tight relationship exists between Fourier transform (FT) and Radon transform (RT) of a function. The 1D FT of n-dimensional RT(f) along the radial direction ρ represents a radial sampling of the n-dimensional FT of *f*. This is the central-slice theorem. With the central-slice theorem the 3D Radon transform can be computed equivalently by performing a 3D DFT, a Cartesian-to-polar mapping, and a 1D DFT. This process requires 3D interpolation in real space which is a computation intensive. The computing cost is substantially reduced in a two-step process. In the first step rotate the structure stepwise around one axis and obtain a set of projections. In the second step compute the 2D Radon transform of each projection.

2.1.3 Particle Swarm Optimization (PSO)

PSO was firstly introduced by Kenny and Eberhart in 1995 [20] it is one of the evolutionary computation technology based on swarm intelligence. In a PSO system each solution called a "particle". Particles fly around in the problem search space to look for the optimal solution. Each particle adjusts its position according to the flying experience of its own and the experience of neighboring particles. Each particle updates its velocity and position using the following equation [21]:-

$$V_i(k+1) = V_i(k)+c1 * \mathit{rand}1(\, pbest(k) - X_i(k)) + c2 * \mathit{rand}2(\, gbest(k) - X_i(k)) \quad (3)$$

$$X_i\,(k+1)=X_i(k) + V_i(k+1) \quad (4)$$

Where ,

V_i	is called the velocity for particle i;
X_i	is represent the position of particle i ;
Pbest	is the best position of ith particle ;
gbest	is the global best position ;
rand	is random variable in [0,1];
c1 and c2	are the learning factors;
w	is called the inertia weight .

To search for optimal solution each particle changes its velocity according to Eq (3). The value of V_i is clamped to the range [Vmin, Vmax] to avoid excessive roaming of particle outside the searching space. Then each particle moves to a new potential solution using Eq. (4). This process is repeated until a stopping criterion is reached. The above equations (3,4) are the basic Equation and not guarantee the global solution is reached and may trapped in local minima. To avoid the local minima there are many variations for the basic equations have been suggested like (QPSO) which adding quantum behavior to basic PSO[22,23,24], (CPSO) which add chaotic[25] through chaos maps to basic PSO also the mixing of the two previous methods is suggested in [23] , There are an efforts to add the crossover and mutation used in GA to be used with PSO which improve its behavior and avoids the local minima[26]. Also a varying dimensional particle swarm optimization (VD-PSO) was proposed by Yanjun Yan[27]. An improved PSO by estimation of distribution was introduced in[28].

Some of PSO applications in the Face Recognition field are feature selection optimization[29], Robust object detection scheme using Binary PSO[30], A Novel Evolutionary Face Recognition using PSO[31], Face Recognition Using shift invariant feature transform and BPSO[32], Face Recognition by Extending EBG matching using PSO[33], using CPSO-SVM in Face Recognition [34], Holistic and partial facial fusion by BPSO[35].

In our project the PSO is used to select the best values of (θ, □) for 3D Radon transform; that achieve the high recognition rate. The range of (θ, □) for 3D Radon transform is (-π to π) but due to symmetry of the transform we can calculate only in range (-π/2 to π/2). Also for discrete RT only the integer values are used. We used the PSO to select the minimum number of angles (θ, □) required to obtain the best recognition rate. A novel method of encoding the parameters (θ, □) within the particle was used which led to a reduced number of computations that are required by 3D Radon.

2.1.4 Wavelet Transform

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function ψ:

$$C(\text{scal}, \text{position}) = \int_{-\infty}^{+\infty} f(t)\psi(\text{scal}, \text{position}) \quad (5)$$

The results of the CWT are many *wavelet coefficients* C which are a function of scale and position calculating wavelet coefficients at every possible scale is a fair amount of work, and it generates an awful lot of data. What if we choose only a subset of scales and positions that if we choose scales and positions based on powers of two so called *dyadic* scales and positions then our analysis will be much more efficient and just as accurate[36]. An efficient way to implement this scheme using filters was developed in 1988 by Mallat. The Mallat algorithm is in fact a classical scheme known in the signal processing community as a *two-channel sub band coder* for many signals and the low-frequency contents is the most important part. It is what gives the signal its identity. On the other hand the high-frequency contents impart flavor or nuance In wavelet analysis. We often speak of *approximations* and *details*. The approximations are the high-scale low-frequency components of the signal. The details are the low-scale high-frequency components see figure (2). In our project only the approximations signal (A) is used and the details signal (D) is ignored this achieves two goals. The first is that the features produced will maintain a high classification rate. The second is the number of features are reduced into one half. The mother wavelet (ψ) used is Daubechies (db1) also known as Harr which has been proven effective for image analysis and feature extraction.

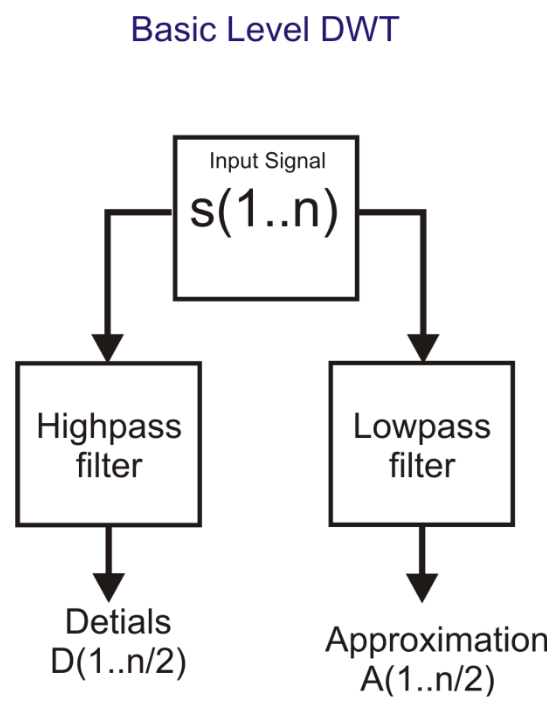

FIGURE 2: Level one Discrete Wavelet Transform (DWT)

2.1.5 Linear Discriminant Analysis (LDA)

The LDA finds a set of basis vectors which maximizes the ratio of the between-class scatter and within–class scatter [37]. Given N samples of C classes and let N_i be the number of samples in the *ith* class(ci). let Mt be the mean of the whole data set and mi be the mean of the *ith* class (ci) then the between-class scatter matrix is defined by:

$$S_B = \sum_{i=1}^{c} N_i(mi - Mt) \quad (mi - Mt)^T \quad (6)$$

And the within-class scatter matrix is defined by

(7)

Then the basis vectors is:

(8)

3. THE EXPERIMENTS

Three different experiments were conducted using Texas 3DFR Database [38]. The Texas 3D Face Recognition Database contains 1149 range and portrait mage pairs of adult human subjects each image is (751 x 501) 8-bit. A Sample image and its 3D representation is shown in figure (3).The database images are scaled down into (94 x 63). Each scaled image is transformed into 3D space as (94, 63, 90) array of real numbers these 3D arrays were transformed into 3D radon space as (90, 90, 90) real numbers. This means that each image is represented as (729000) real numbers. A features vector of length (90) real numbers was selected from (72900) real numbers by using PSO. Those (90) value vectors was further reduced into (45) value vectors after Wavelet Transform. These feature vectors were projected into the maximized discrimination projection using the Linear Discriminante Analysis (LDA) and stored into the database .

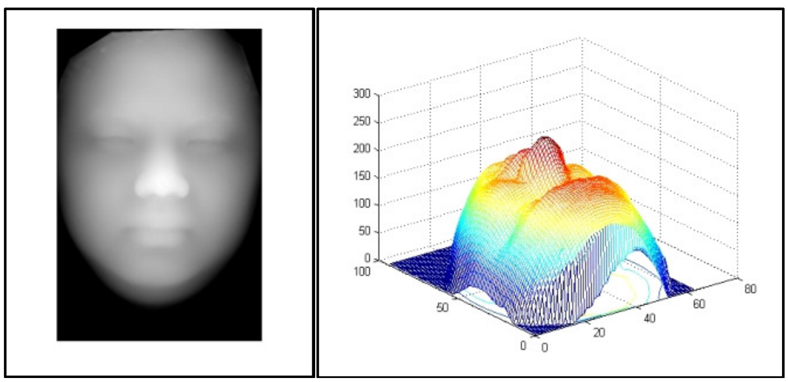

FIGURE 3: left one is the Range Image and right one is the 3D representation of the left.

3.1. Experiment No.1

In this experiment 100 subjects were selected with two different images for each subject one for the gallery and one as a probe image for testing. In this experiment the LDA stage is not used because there is only one sample per class is used. The other stages depicted in fig(1) were used. The recognition rate achieved conducting this experiment was RR=86% .

3.2. Experiment No.2

In this experiment 18 subjects were selected with 10 images per subject as a gallery and more than 10 images as a probe. The gallery set and probe set are disjoint; see figures (4, 5). The complete system was used In this experiment. The recognition rate achieved was 100%.

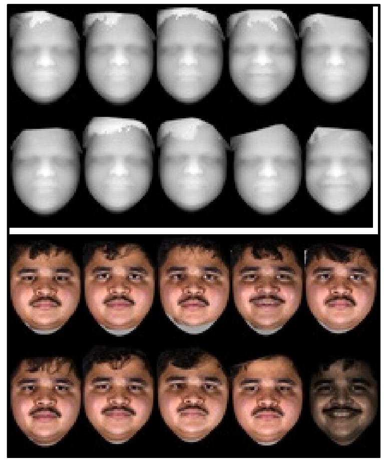

FIGURE 4: The upper 10 range images are a samples of images for a person used in the gallery , the lower 10 are the portrait for the same range images in the upper part.

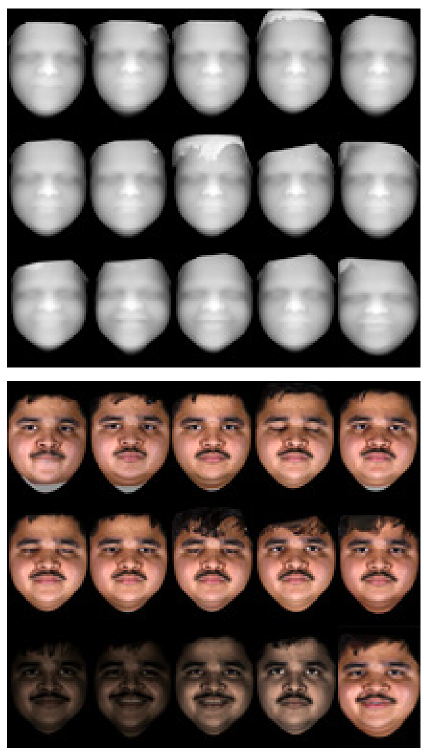

FIGURE 5: The upper range images are a samples of images for a person used as Probes , the lower are the portraits for the same range images in the upper part.

3.3. Experiment No.3

In this experiment an (18) subjects were used with 10 images per subject as a gallery. The probe set was composed of 180 images for authorized users and 180 image for imposters (not authorized). All sets were disjoint . The Receiver Operating Condition ROC was illustrated by the figure(6). The verification rate is 98.34% or (FRR=1.66% , at zero FAR).

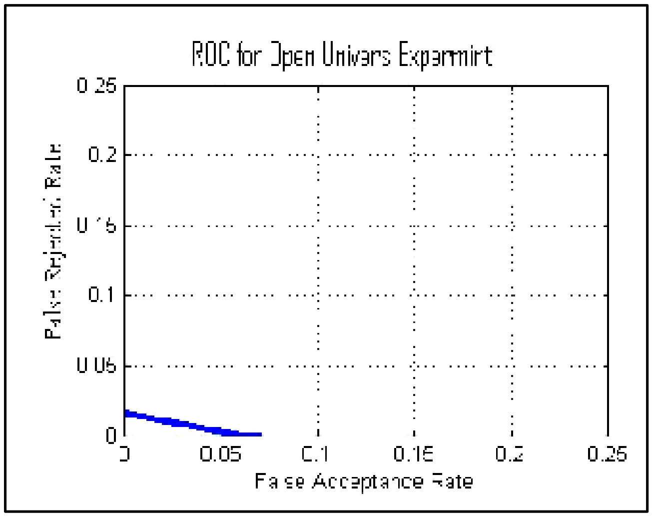

FIGURE 6: Receiver Operating Condition for experiment 3

4. DISCUSSION AND COMPARATIVES

The first and second experiments are recognition test for our method and the third one is for verification test. The results are promise and even the comparison in not easy task because the many differences between evaluation scenarios due to the different data set available and different scenarios in partitioning those data sets between training and gallery and probe data sets but we can depict the validity of our work as following

A. The first and second experiments can be compared with some related works as shown in table(1). Some works used a controlled environment for the data set (i.e. equal in illumination and pose and expression) some other not. The images we used are selected randomly from the data base with different conditions.
B. The third experiment can be compared with some related works as shown in table(2). Some of them follow the Face Recognition Grand Challenge (FRGC V2.0) ROC III protocol they report the False Rejection Rate (FRR) at False Acceptance Rate (FAR) equal to 0.1%. We report the Equal Error Rate (EER=1.3%) and the FRR=1.64% at FAR=0.1% and FRR=1.66% at FAR=0%.

All the experiments are carried out using MATLAB software R2010a on a laptop computer with i3 CORE @ 2.4 GHz speed and 2 GB RAM. The time required to process one image approximately equal to 5.56 msec and to process all the 180 images to be stored in the gallery was approximate to 1 sec. The recognition or verification time is a faction of second and depends on the size of the data base used which must be investigated further. Also this method need to be tested on large data set that agrees with the used scenario to test its validity.

author	database	#subject	#Training images	#Gallery images	#Probe images	Performance
Chang[41]	Notre Dame	166	278	1/subject controlled	1/subject controlled	RR= 83.7%
Godil [42]	CAESAR	200	-	1/subject	1/subject	RR= 68%
Gupta[40]	Texas 3DFR	12	360	1/subject neutral	29/subject	RR= 98.6%
Gupta[39]	Texas 3DFR	105	-	1/subject neutral	663	RR=98.64%
Our experiment(1)	Texas 3DFR	100	No training	1/subject uncontrolled	1/subject uncontrolled	RR = 86%
Our experiment(2)	Texas 3DFR	18	180	10/subject uncontrolled	10+/subject uncontrolled	RR=100%

TABLE 1: A Comparison between some reported Face Recognition rates and the recognition rate in experiment 1&2.

Author	#subjects	#Gallery images	#Probe images	Performance
Passalis [15]	466 FRGC v0.2	4007	4007	FRR = 3.6% FAR = 0.1%
Husken [43]	466 FRGC v0.2	4007	4007	FRR = 2.7% FAR = 0.1%
Maurer [44]	466 FRGC v0.2	4007	4007	FRR = 6.5% FAR = 0.1%
Jahanbin[16]	109	109	382 + 424 imposters	EER= 2.2%
Our experiment(3)	18	180	180 + 180 imposters	FRR=1.64% FAR=0.1% EER=1.3%

TABLE 2: Comprison between some reported Face Verification rates and the Verification rate in experiment 3.

5. CONCLUSIONS

In this work an Improved 3D Mixed Transform (3D IMT) is used for 3D face recognition. The 3D mixed Transform is also known as 3D Ridgelet Transform. It is composed of 3D Radon Transform (3DRT) plus 1D Wavelet Transform. The 3D Radon that we are used is Fourier based. This transform is improved by using (PSO) to select the best directions (θ, □) along which the 3DRT is performed. By this method the number of features is reduced to a vector of (45) elements as well as achieved a maximized discrimination based on the Linear Discriminant Analysis (LDA) as a consequence this leads to a high recognition rate. Three experiments were conducted:

1. In the first experiment a single image per person (i.e. a vector of 45 elements) is stored in the database and another one is used for testing. The gallery set and probe set were disjoined. The number of subjects used were 100 and the recognition rate was RR=86%.
2. In the second experiment ten images per person are used for training and more than ten for testing. All images have different expressions, illuminations and poses. The training and testing sets are non-overlapped. The number of subjects used were 18 subjects and the recognition rate was RR=100%.
3. The third experiment was the same of the experiment 2 but the test set was different. Her test set contains 180 imposters (no subject is stored in the database) and 180 images of authorized subjects (stored in the database). The Receiver Operating Condition (ROC) is illustrated in figure (6). The verification rate is 98.34% or (False Rejection Rate (FRR) =1.66 % at zero False Acceptance Rate).

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