Pose-Invariant Multimodal (2D+3D) Face Recognition using Geodesic Distance Map

Farshid Hajati [1,2], Abolghasem A. Raie [1], Yongsheng Gao [2,3]

[1.] Electrical Engineering Department, Amirkabir University of Technology, Tehran 15914, Iran
[2.] School of Engineering, Griffith University, QLD 4111, Australia
[3.] Queensland Research Lab, National ICT Australia, QLD 4207, Australia
hajati@aut.ac.ir, raie@aut.ac.ir, yongsheng.gao@griffith.edu.au

Abstract: In this paper, an efficient pose-invariant face recognition method is proposed. This method is multimodal means that it uses 2D (color) and 3D (depth) information of a face for recognition. In the first step, the geodesic distances of all face points from a reference point are computed. Then, the face points are mapped from the 3D space to a new 2D space. The proposed mapping is robust under the in-depth face rotations. Finally, the feature extraction and face classification task is done in the new 2D space. For feature extraction, we use the Patch Pseudo Zernike Moments (PPZM) with a new weighting method to decline the self-occlusion caused by in-depth rotations. For this purpose, a novel approach for self-occlusion detection based on geodesic distances of face points is proposed and a self-occlusion map is created. For evaluation purpose, a large scale 3D face database is used and the various in-depth rotations (vertical and horizontal) are tested. The performance of the proposed method in two scenarios is compared with a classical 3D face recognition method. The results emphasize the performance of the proposed method in the pose-invariant face recognition.
[Farshid Hajati, Abolghasem A. Raie. Pose-Invariant Multimodal (2D+3D) Face Recognition using Geodesic Distance Map. Journal of American Science 2011;7(10):583-590]. (ISSN: 1545-1003). http://www.americanscience.org.

Keywords: Face recognition; geodesic; pose

1. Introduction

Biometrics is the science of verifying or identifying people. Verification is performed by matching an individual’s biometric characteristic with a reference biometric characteristic to measure the similarity. Identification, however, is performed by matching an individual’s biometric characteristic with all identity templates in the gallery set. Because the human face is a nonintrusive biometric characteristic, it is more acceptable for people than the others (Jain et al., 2004). On the other hand, face recognition is a challenging task because of the variety in expression, age, pose, illumination, and occlusion (Abate et al., 2007). The face recognition algorithms are divided in three categories based on the type of data they use. The first category consists of 2D face recognition algorithms. These algorithms use 2D images for recognition task. 2D face recognition algorithms have a good performance under controlled conditions such as illumination and pose. But, their performance reduces in the presence of illumination and posture variations (Romdhani et al., 2006). A comprehensive survey of 2D face recognition algorithms is given in (Zhao et al., 2003). The algorithms which use 3D scans are in the second category. These algorithms are called 3D face recognition. Because of the fact that face is a 3D object whose 3D features is invariant under the illumination and pose variations, using 3D information of the face can improve the face recognition performance. In fact, 3D features represent the intrinsic structure of the face, while 2D features are extrinsic and may vary due to the environment changes.

The third category consists of multimodal face recognition algorithms which use both 2D and 3D facial data. Generally, existing approaches in the multimodal face recognition perform separate matching on 2D and 3D face data and then fuse the results to improve the recognition rate. Marvridis (2001) incorporated a range map of the face into a classical face recognition algorithm based on PCA. He compensated the face rotation and applied the PCA algorithm on both 2D and 3D data and classified the faces based on the concatenated vector from two data. Chang (2003) used a PCA-based approach for separate 2D and 3D face recognition and fused the matching scores. He reported a recognition rate of 93 percent and 99 percent for 3D and multimodal face recognition, respectively, using a gallery of 275 people. Lu (2006) used feature detection and registration with the ICP algorithm (Besl et al., 1992) in the 3D domain and LDA in the 2D space for multimodal face recognition. He performs the recognition task in pose variation by matching 2.5D face scans to complete 3D face models. He reported a multimodal recognition rate of 99 percent for neutral faces and 77 percent for smiling faces using a database of 200 gallery and 598 probe images. Bronstein (2005) proposed an expression-invariant multimodal face recognition algorithm. This approach relies on the assumption that the face is approximately isometric, which means that geodesic distances among points on the surface are preserved in different expressions. Mpiperis (2007) proposed an expression-invariant face recognition method based on geodesic distances of face points. He proposed a polar representation of face to represent face points in 3D space. Experiments were performed on two databases. The first database consists of 2500 3D models belonging to 100 subjects and the second database is recorded from 70 people, depicting common moderate expressions. The recognition rates were 84.4 percent and 95 percent for both databases, respectively.

In this paper, we propose an efficient multimodal pose-invariant face recognition method which uses geodesic distances between face points. This method is based on the fact that the geodesic distances between face points are preserved under the pose variation. The feasibility and effectiveness of the proposed method has been investigated using a wide range of experiments. The encouraging experimental results show that the proposed method has better performance compare with the benchmark.

The sequel of this paper is organized as follows: the next section presents the overview of the proposed face recognition system and geodesic mapping method. Towards the end of this paper, the feature extraction and classification method, the experimental results and discussions are presented.

2. Material and Methods

2.1 Proposed Face Recognition System Overview and Geodesic Mapping Method

The scheme of the proposed face recognition system is depicted in Figure 1. The proposed face recognition system consists of two main blocks. In the first block, a new mapping based on face geodesic distances is used to map face surface points to a 2D image. Another image which is called "Geodesic Distance Map" (GDM) is computed in the first block. In the second block, we use an adaptive weighted patch moment array proposed by Kanan (2008) for feature extraction from mapped 2D images and do the recognition task based on extracted features. The detail of the proposed method will be described in the following.

We use the geodesic distances of face points to map them from the 3D space to a 2D image. At first, the geodesic distance of face points from a reference point should be computed. We can choose each surface point as the reference. But, if we like to have a mapping in the presence of pose variations, we should choose a suitable point which appears in different postures. Hence, in this paper the nose tip point is selected as the reference point. Moreover, the nose tip can be extracted more easily in comparison with the other face points.

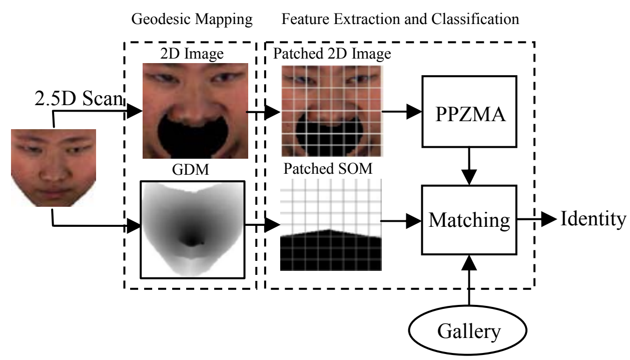
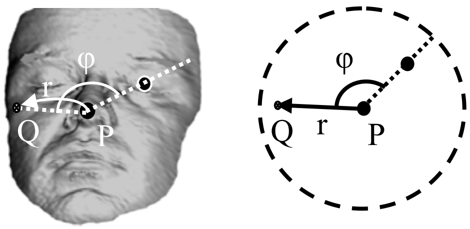


Figure 1. Proposed face recognition system scheme

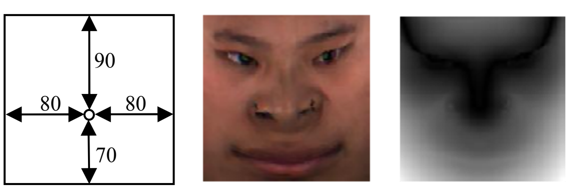
After computing the geodesic distance of all face points from the nose tip, we should set a coordinate system based on the computed geodesic distances to represent face points. In order to have a pose invariant mapping, we need to have a rotation invariant coordinate system. In this research, we use a new geodesic coordinate system in which each face point has a unique magnitude (r) and argument (φ). For this purpose, the geodesic distance of each point from the reference point (nose tip) is considered as the magnitude in the coordinate system. On the grounds that geodesic distances between face points are constant by face rotation, the defined magnitude is constant under the face rotations. To determine a constant argument in different rotations, we need a fixed reference plane in 3D space. In this paper, the plane which crosses three points nose tip, right eye, and left eye is defined as the reference plane. For selection of these points two advantages are considered: 1) the mentioned points can appear in different rotations up to 45 degrees, 2) there are some techniques to extract these points in the 3D face space (Lu et al., 2006). By assuming the mentioned reference plane, the argument of each point can be defined as the following: the argument of each point is the angle between two planes; one is a plane crosses the point and nose tip and is perpendicular to the reference plane and another is a plane crosses the left eye and nose tip and is perpendicular to the reference plane (Figure 2a). In other words, to compute the argument of each point, we should project each point on the reference plane. Then, the angle between the line connecting projected point and nose tip and the line connecting left eye and nose tip is considered as the argument. Because of the fact that the location of face points is fixed respect to reference plane, the computed arguments are constant with face rotation. By using the magnitude and argument of all face points, we can define a mapping from the 3D space to a 2D space. For this purpose, each point is represented by its magnitude (r) and argument (φ) on a 2D polar plane. In the 2D polar plane, r is the Euclidean distance from the pole (P) and φ is the angle between the radius connects the point and the radius connects the left eye (see Figure 2b).



(a) (b)

Figure 2. a) defining magnitude and argument of a point, b) mapping a point to the 2D polar plane

After finding the location of points in the 2D polar plane, we should represent each point with a feature from original 3D space. To do that, two features can be used: the color of the point and the depth (range) of the point. For using color, the color of each point is dedicated in the 2D polar plane. On the other hand, we consider the distance of point from the reference plane (the plane which crosses from nose tip, left eye, and right eye) as its depth. By this definition the depth of the points is constant under face rotations. After mapping all points to the polar plane, we should crop the mapped 2D image to obtain the face rectangle which contains eyes, nose, and mouth of the person. For this purpose, we first rescale each mapped image in a way that the distance between eyes is 80 pixels. Then, we crop image based on the model shown in Figure 3a. An example of applying the proposed mapping is showed in Figure 3b and Figure 3c.

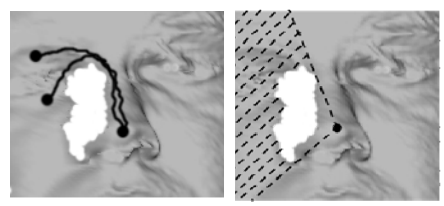


(a) (b) (c)

Figure 3. a) the cropping model, b) 2D mapped image with color feature, c) 2D mapped image with depth feature

A main problem in pose-invariant face recognition is the self-occlusion. When a face rotates respect to the camera, some parts of the face may disappear in the captured image. Self-occlusion in face images can affect the performance of the proposed face recognition system in two ways; not only some parts of the face may disappear because of self-occlusion, but also some "holes" will appear in the face surface. The location of these holes especially is around of the nose (see Figure 4). The geodesic distance of some face points can increase by a hole in the face surface (Figure 5a). This increase in geodesic distances will happen for a region of the face which located after the hole. This region is depicted in Figure 5b by shadowing.

Figure 4. a hole in face surface because of self-occlusion



(a) (b)

Figure 5. a) increase in geodesic distances because of the hole, b) the region of invalid geodesic distance

It is clear that this increase in geodesic distances can affect our mapping by increasing the magnitude (r) of the points located in the shadowed region in figure 5b. This increase results in degradation in 2D mapped image result. Experiments show that this degradation can reduce the performance of the recognition system. To overcome this reduction, we should find the degradation region and decline its influence in the recognition system.

In order to handle the self-occlusion problem, a "Self Occlusion Map" (SOM) which shows the parts with invalid geodesic distance is created. To create a SOM, we compute a "Geodesic Distance Map" (GDM) of each face. This GDM is a grayscale image in which each pixel represents the geodesic distance of that coordinates. In order to create such image, all face points are projected onto the reference plane crossing three points nose tip, right eye, and left eye. For each projected point the value of its geodesic distance is dedicated. As an illustration, a sample of GDM is depicted in Figure 6a. For displaying purpose, we rescaled the image pixels to the range of [0, 255]. By using the GDM we can detect the self-occlusions in face surface. For this purpose, we use the geodesic distance gradient in face surface based on GDM. In a GDM, the pixel value is black (0) in the nose tip coordinates and increases by the distance from the nose tip. The model of gradient directions is shown in Figure 6b. On the grounds that the self-occlusion increases the geodesic distance abruptly along the showed directions, the boundary of self-occlusion can be detected by finding the abrupt changes along the gradient directions.

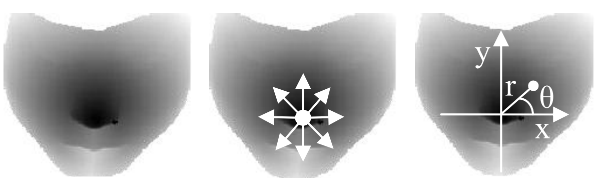
Let assume that f(x,y) represented a continuous GDM. To find the abrupt changes in geodesic distance gradient, we can measure the gradient of f(x,y) along the r in a polar coordinates (see Figure 6c) by

$$\frac{\partial f(x,y)}{\partial r}=\frac{\partial f(x,y)}{\partial x}\frac{\partial x}{\partial r}+\frac{\partial f(x,y)}{\partial y}\frac{\partial y}{\partial r} \quad (1)$$
$$=f_x(x,y)\cos\theta+f_y(x,y)\sin\theta$$

In a digital GDM, f(m,n), the above gradient can be implemented as

$$g_k(m,n)=h_k(-m,-n)*f(m,n) \qquad 1\le k\le 8 \quad (2)$$
$$g(m,n)\triangleq\max_k\{|g_k(m,n)|\} \quad (3)$$

where g(m,n) is the gradient of f(m,n) and h_k's are the eight masks shown in Figure 7. h_k is a mask corresponding to the gradient direction $\theta_k=\pi/2+k\,\pi/4$.



(a) (b) (c)

Figure 6. a) geodesic distance map, b) gradient direction model, c) polar coordinates in GDM

After applying the above gradient algorithm, the boundary of self-occlusion in the face surface is extracted (Figure 8a). By using the self-occlusion boundary, we can determine a sector of the face in which the geodesic distances are not valid. This sector is defined by the nose tip and self- occlusion boundary. After determining the mentioned sector, we should map its boundary to our 2D space. Now, by using the mapped boundary we can create a SOM for the mapped face in which the invalid part is shown as black (zeros) and valid part is shown as white (ones). A sample of the SOM is shown in Figure 8b.

$$\begin{pmatrix}1&1&1\\0&0&0\\-1&-1&-1\end{pmatrix}\begin{pmatrix}1&1&0\\1&0&-1\\0&-1&-1\end{pmatrix}\begin{pmatrix}1&0&-1\\1&0&-1\\1&0&-1\end{pmatrix}\begin{pmatrix}0&-1&-1\\1&0&-1\\1&1&0\end{pmatrix}$$
$$\begin{pmatrix}-1&-1&-1\\0&0&0\\1&1&1\end{pmatrix}\begin{pmatrix}-1&-1&0\\-1&0&1\\0&1&1\end{pmatrix}\begin{pmatrix}-1&0&1\\-1&0&1\\-1&0&1\end{pmatrix}\begin{pmatrix}0&1&1\\-1&0&1\\-1&-1&0\end{pmatrix}$$

Figure 7. Eight gradient masks

(a) (b)

Figure 8. a) self-occlusion boundary, b) Self Occlusion Map (SOM)

2.2 Feature Extraction and Classification

In order to complete the face recognition procedure we should extract some features from the 2D mapped images and classify them. In this paper, Patch Pseudo Zernike Moments (PPZM) originally proposed by Kanan (2008) are used to extract features. To extract these features, the 2D mapped image is partitioned into a set of equal-sized patches in a non-overlapping way. Then, PPZMs are extracted from each patch of the partitioned face image and are concatenated to form a Patch Pseudo Zernike Moment Array. The advantages of the pseudo Zernike moments are that they are shift, rotation and scale invariant and very robust in the presence of noise. Pseudo Zernike polynomials are orthogonal sets of complex-valued polynomials. If a 2D image is represented as f(x,y), The two-dimensional complex PZMs of order n with repetition m are defined as

$$PZM_{n,m}(f(x,y))=\frac{n+1}{\pi}\iint_{x^2+y^2\le 1}V^*_{n,m}(x,y)f(x,y)\,dxdy$$
(4)

$$V_{nm}(x,y)=R_{nm}(x,y)\exp(jm\tan^{-1}(\frac{y}{x})) \quad (5)$$

where $n\ge 0$, $|m|\le n$ and radial polynomials, R_{nm}, are defined as:

$$R_{nm}(x,y)=\sum_{s=0}^{n-|m|} D_{n,|m|,s}(x^2+y^2)^{\frac{n-s}{2}} \quad (6)$$

where

$$D_{n,|m|,s}=(-1)^s\frac{(2n+1-s)!}{s!(n-|m|-s)!(n-|m|-s+1)!} \quad (7)$$

In order to use PPZM technique the 2D mapped images should partitioned into a set of equal-sized patches (see Figure 9).

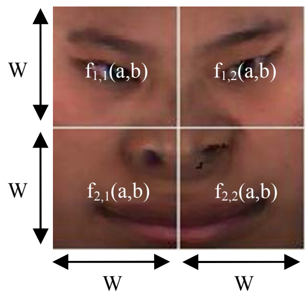


Figure 9. Image partitioning in PPZM technique

After After partitioning, PPZM of order n with repetition m of a continuous image intensity function f(x,y) can be defined as

$$PPZM_{n,m}^{p,q}(f(x,y))= \frac{n+1}{\pi}\iint_{x^2+y^2\le 1} V_{n,m}^{*}(x,y)f(W(p-1)+a,W(q-1)+b)dxdy \quad (8)$$

where W is the patch size, p and q are integers ranging from 1 to N/W (the size of the image is N×N) indicating the location of the patch. Since $\left|PPZM_{n,-m}^{p,q}\right|=\left|PPZM_{n,m}^{*p,q}\right|=\left|PPZM_{n,m}^{p,q}\right|$, the magnitudes of PPZMs of order n=0 up to n_{max} with $m \ge 0$ is considered as moment features. Finally, the extracted PPZMs are concatenated to form a PPZM array (PPZMA) as

$$PPZMA[f(x,y)]=\left\{ \overset{n_{max}}{PPZM}[f_{p,q}(a,b)\Big| p,q=1,2,...,\frac{N}{W} \right\}$$

(9)

After extracting PPZMA we can use it as a feature vector to classify images. But, as mentioned the geodesic distance and mapped images can have some degradation because of self-occlusion. Using the SOM, we can specify the contribution of each patch in the classification stage. For this purpose, the SOM of the face is patched in a way as describe above. Then, the average of each patch pixel values is used as a coefficient for feature vector weighting. Based on the above image representation, a face is described by a PPZMA associated with a SOM. For a given query face, the face recognition process generates the PPZMA descriptor of the query face and calculates the weighted Euclidean distance between the query PPZMA descriptor and the model PPZMA descriptor in the database

$$d=\left\|\overrightarrow{SOP}\bullet((\overrightarrow{PPZMA(f(x,y))}-\overrightarrow{PPZMA(h(x,y))})\right\| \quad (10)$$

where • is the inner product, f(x,y) and h(x,y) are the query and face models, respectively.

3. Results

In order to evaluate the performance of the proposed system in pose-invariant face recognition, an extensive experimental investigation is used, covering face recognition under a variety range of rotation angles. The experiments were conducted on the BJUT3D face database which contains 500 3D face models from 500 people (250 men and 250 women). The 3D face original data were captured through a laser scanner. The scanner can get the precise shape and color texture at one time. It records the shape information in cylinder coordination, and there are 489 sampling points in the circle direction, and 478 sampling points in axis direction. The scanning radius ranges from 260mm to 340mm, and every sampling point is corresponding with a 24-bit texture point which is saved as a texture image of points. The data is very precise captured by the scanner. Everyone's original data is made up of 200,000 points and 400,000 triangle faces. Because there is only a 3D model for each person in our database, we should synthesize new 2.5D face scans in desired view angles. For this purpose, the original 3D face models are rotated in preferred angle and 2.5D face scans are synthesized. In this procedure, the self-occlusion parts of the face should be considered. In this paper, the angles of 15, 25, 35, and 45 degrees in horizon and vertical are considered. For horizontal and vertical rotations 3D face models are rotated around the y-axis and x-axis in 3D space, respectively. These angles are depicted in Figure 10.

To evaluate our system, we use a gallery consists of 500 2.5D scans from 500 people (one image per person). All gallery scans are frontal. On the other hand, there are 12 scans for each person in probe set. These 12 images are corresponding to 12 different poses depicted in Figure 10.

In the first experiment, the parameters of feature extraction method should be computed. These parameters are the maximum PPZM's order (n_{max}) and the size of the patch window (W). For this purpose, we compute the rank-1 recognition rate of the proposed system in one of the rotation angles (e.g. 45° clockwise rotation around x-axis) with different n_{max} and W. In this experiment, we selected the n_{max}=1, 2, …, 8 and W=4, 8, 16, 32. In order to select the mentioned parameters more precisely, we also measured the run time of the system in each case. The obtained recognition rates and run times versus n_{max} are plotted in Figure 11. The results obtained by the Intel Cor2Due 2.5 GHz processor with MATLAB 7.2. As can be seen, the recognition rate has some fluctuations with W=4, 8; while, the run time increases. On the other hand, the recognition rate for W=16 reaches around 99.6 percent for n_{max}=5 and then remains constant. The run time of the system with W=16 and n_{max}=5 is about 50 seconds. The recognition rate for W=32 is declined significantly. To have an optimum recognition rate with a short run time we should W=16 and n_{max}=5.

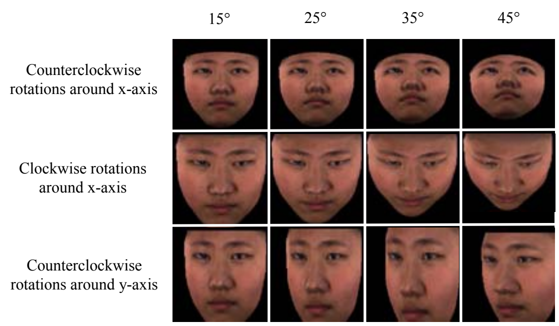


Figure 10. 2.5D scans in different rotation angles in horizon and vertical

In the second experiment, the recognition rate of the system was measured in all rotation angles with the parameters of W=16 and n_{max}=5 obtained in the first experiment. In order to show the performance of the proposed algorithm, we used three scenarios: 1) the proposed algorithm using color information, 2) the proposed algorithm using depth information, 3) using 2D and 3D information by the HISCORE algorithm proposed by Marvidis (2001). Marvidis in HISCORE algorithm estimated the rotation angle of the input 2.5D face scan and compensated it to yield a frontal face scan. Then, he applied the PCA method in 2D and 3D spaces to create two feature vectors for each face scan. Finally, he obtained a feature vector by concatenating the feature vectors. In this paper, we developed HISCORE on our database with the assuming that the rotation angle of input face scans is known. So, the error of rotation assessment has been eliminated in HISCORE results in scenario 3.

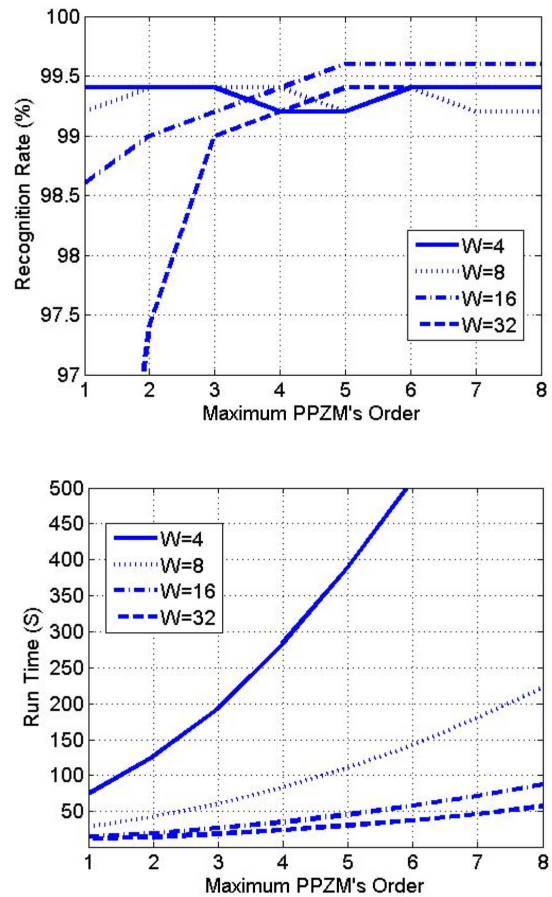


Figure 11. The recognition rate and run time of the system with different n_{max} and W values

In this research, we use popular Principal Component Analysis (PCA) method (Turk and Pentland, 1991) to classify mapped 2D images in scenario 1 and 2. First, the images of gallery set are used to build an eigenspace. Then, each probe image mapped to this eigenspace in the same way and its Euclidean distance to each gallery images is computed. In this paper, the inverse of Euclidean distance is used as matching criteria. The matching results between each probe image and all gallery images are used to measure the rank-1 recognition rates in each rotation angle. The results for counterclockwise rotation around y-axis, counterclockwise rotation around x-axis, and clockwise rotation around x-axis are sown in table 1, 2, and 3, respectively.

Table 1. The rank-1 recognition rates in counterclockwise rotations around y-axis

	y-15 Right	y-25 Right	y-35 Right	y-45 Right
Scenario 1	100	100	100	100
Scenario 2	99.8	98.6	97.4	96.2
Scenario 3	98	93.2	89.4	80.2

Table 2. The rank-1 recognition rates in counterclockwise rotations around x-axis

	x-15 Up	x-25 Up	x-35 Up	x-45 Up
Scenario 1	100	100	100	100
Scenario 2	100	100	99.8	92.6
Scenario 3	100	100	100	98.8

Table 3. The rank-1 recognition rates in clockwise rotations around x-axis

	x-15 Down	x-25 Down	x-35 Down	x-45 Down
Scenario 1	99.8	98.4	98.8	99.6
Scenario 2	56	19.8	13.2	12.8
Scenario 3	99.6	98.2	97.6	97.6

For counterclockwise rotations around y-axis, the recognition rate in scenario 1 is 100 percent for all rotation angles. While, the recognition rates are 99.8, 98.6, 97.4, and 96.2 percent in scenario 2 and 98, 93.2, 89.4, and 80.2 percent in scenario 3. Moreover, using color information has a better performance in our algorithm than using the depth information. The recognition rates in clockwise rotations around x-axis are better than the previous case. Because of the face structure in counterclockwise rotations around x-axis the self-occlusion is less than the counterclockwise rotations around y-axis. So, the yielded holes are smaller and the degradation is negligible. The recognition rates are better in the proposed algorithm with color information. In clockwise rotations around x-axis, The proposed system has a recognition rate of 99.8, 98.4, 98.8, and 99.6 percent for 15, 25, 35, and 45 degrees in scenario 1. These rates are 56, 19.8, 13.2, and 12.8 percent in scenario 2. Moreover, the recognition rates are 99.6, 98.2, 97.6, and 97.6 percent in scenario 3. These rates show that the performance of the proposed system in two scenarios 1 and 2 is better than the HISCORE. Also, we can say that it is more efficient for proposed system to use color information instead of depth information.

4. Discussions

In this paper, a new pose invariant multimodal face recognition technique has been presented. This technique uses a mapping based on geodesic distances between face points. Because the parameters of the mapping are computed based on the face plane the proposed mapping is robust under face rotations. To decline the effect of self-occlusion in face rotations, a novel self-occlusion map and Patch Pseudo Zernike Moments (PPZM) are used. For evaluation purpose, a large scale 3D face database is used and various in-depth rotations around x and y axes are tested. In order to test the proposed approach, three scenarios considered in experiments. The results showed that the proposed approach was very robust under the face rotations around x and y axes. Also, Experiments showed that using color information has a better performance in our approach than the depth information.

Corresponding Author:
Dr. Farshid Hajati
Electrical Engineering Department, Amirkabir University of Technology, No. 424, Hafez Avenue, Tehran, Iran.
Tel: +98 21 64543365, Fax: +98 21 64543300
Email: hajati@aut.ac.ir

References

1. Jain AK, Ross A, Prabhakar S. An introduction to biometric recognition. IEEE Trans. Circuits and Systems for Video Technology 2004:14(1):4-20.
2. Abate AF, Nappi M, Riccio D, Sabatino G. 2D and 3D face recognition: a survey. Pattern Recognition Letters 2007:(28):1885-1906.
3. Romdhani S, Ho J, Vetter T, Kriegman DJ. Face recognition using 3D models: pose and illumination. Proceedings of the IEEE 2006:94(11):1977-1999.
4. Zhao W, Chellappa R, Phillips PJ, Rosenfeld A. Face recognition: a literature survey. ACM Computing Surveys 2003:35(4):399-458.
5. Marvidis N, Tsalakanidou F, Pantazis D, Malassiotis S, Strintzis MG. The HISCORE face recognition application: affordable desktop face recognition based on a novel 3D camera. Proceeding of International Conference on Augmented Virtual Environments and 3D Imaging, 2001.
6. Chang KI, Bowyer KW, Flynn PJ. Face recognition using 2D and 3D facial data. Proc. Workshop Multimodal User Authentication, 2003:25-32.

7. Lu X, Jain AK, Colbry D. Matching 2.5D scans to 3D models. IEEE Trans. Pattern Analysis and Machine Intelligence 2006:28(1):31-43.
8. Besl PJ, McKay ND. Reconstruction of real–world objects via simultaneous registration and robust combination of multiple range images. IEEE Trans. Pattern Analysis and Machine Intelligence 1992:14(2):239-256.
9. Bronstein AM, Bronstein MM, Kimmel R. Three–dimensional face recognition. International Journal of Computer Vision 2005:64(1):5-30.
10. Mpiperis I, Malassiotis S, Strintzis MG. 3D face recognition with the geodesic polar representation. IEEE Transactions on Information Forensics and Security 2007:2(3):537-547.
11. Kanan HR, Faez K, Gao Y. Face recognition using adaptively weighted patch PZM array from a single exemplar image per person. Pattern Recognition 2008:(41):3799-3812.
12. Turk M, Pentland A. Eigenfaces for recognition. Journal of Cognitive Neuroscience 1991:3(1): 71-86.

9/19/2011