3D Face Recognition using Gaussian Hermite Moments

Naouar Belghini
Faculty of Technical Sciences
B.P. 2202 – Road of Imouzzer
Fez – Morocco

Arsalane Zarghili
Faculty of Technical Sciences
B.P. 2202 – Road of Imouzzer
Fez – Morocco

Jamal Kharroubi
Faculty of Technical Sciences
B.P. 2202 – Road of Imouzzer
Fez – Morocco

ABSTRACT
Face recognition is an interesting issue in pattern recognition. In this paper, we propose a method for face recognition using 3D depth information. The goal is to get minimum features and produce a good recognition rates. We extract 3D clouds points from 3d vrml face Database, then the nose tip for each sample is detected and considered as new origin of the coordinate system, Gaussian Hermite Moments are applied to characterize each individual and Back propagation neural network is applied for the recognition task. Experimental results shows that Gaussian Hermite moments with global depth information perform significantly better than another method based on local depth information, in this study we consider the case of using ratios of distances and angles between manually selected facial fiducial points.

General Terms
3D Face recognition, Moments, Neural network.

Keywords
Gaussian Hermite Moments, 3D Face Recognition, Back Propagation Neural network.

1. INTRODUCTION
Among the many biometric identication modalities, face recognition is high in the list of subject preference because of its non-intrusive nature. However, from the operator's point of view, face recognition faces some significant challenges like the variety in expression, age, pose, illumination, and occlusion. Many researches have been dealing with this subject and have been trying to find an optimal method with good face recognition rate. In the Vendor Test 2006 the performance of different commercial face recognition methods are compared [1]. The face recognition methods are divided in three categories based on the type of data they use. The first category is 2D methods. These methods have a good performance under controlled conditions. Methods that use 3D information are in the second category. The third category consists in combining both 2D and 3D facial data. A survey of these methods is given in[2][3].

Recently, with the rapid development of 3D acquisition equipment, 3D capture is becoming easier, faster and immune to illumination variation. For 3D face recognition approaches, we can distinguish: global, performing face matching based on the whole face, but it is computationally expensive. And local, that partitions the face surface into regions and extracts appropriate descriptors for each of them.

3D face recognition usually explores depth information and surface features to characterize an individual [4][5][6].

Some other approaches reporte about the relevance of individual regions based on geometric properties of local facial landmarks/fiducial points, and Euclidean distances, ratios of distances, or angles between them have been developed. For example in[7] Fifty-three non-independent features representation have been extracted from twelve anchor points. These multiple features are recognized from the local depth information of distance and angle calculation. In [8] Gupta et al. identify the 20 most discriminatory anthropometric Euclidean and geodesic distance features extracted from the existing literature on anthropometric facial proportions.

Orthogonal moments have been used as powerful tools in pattern recognition and image processing applications.[9][10]. Gaussian-Hermite moments was used to obtain geometric invariant, which provide rich representation due to their mathematical orthogonality and effectiveness in characterizing local details of the signal[11]. Xu et al. proposed Gaussian Hermite moments as local descriptors combined with a global mesh [12].

In this paper, global features based on Gaussian-Hermite Moments are extracted to represent facial data. Experimental results are compared with a local method based on the calculation of distances and angles got from fiducial point identified around the nose and eyes regions.

The remainder of this paper is organized as follows. Section 2 describes the process of feature extraction vectors. Gaussian Hermite Moments are described in Section 3. Sections 4 and 5 report the recognition process and experimental results respectively. Finally, Section 6 summarizes this paper.

2. FACIAL FEATURES EXTRACTION
Habitually, nose is always assumed as the nearest point to the camera, and therefore the highest value in z-axis. Although it can largely reduce the complexity of an algorithm, this assumption does not always hold (like some examples in Fig 1). To handle with that, we propose to limit the search of the nose tip in the 2/3 part of the model.

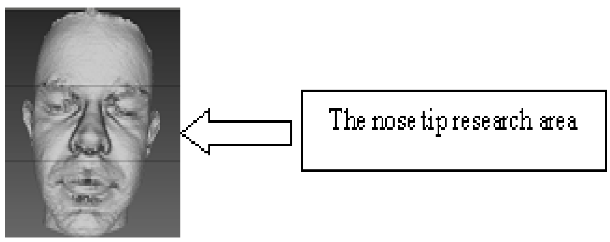

Fig 1: the nose tip research area

After the detection of the nose tip point, we consider the obtained point as new origin of our coordinate system. We consider the global geometric features as follows:

$V = \{Z(p_1), Z(p_2), \ldots, Z(p_n)\}$. where $Z(p_i)$ is the Z-coordinate of the point p_i in the mesh model. Then we reduce the dimension of the extracted vector using the average value for each 50 points.

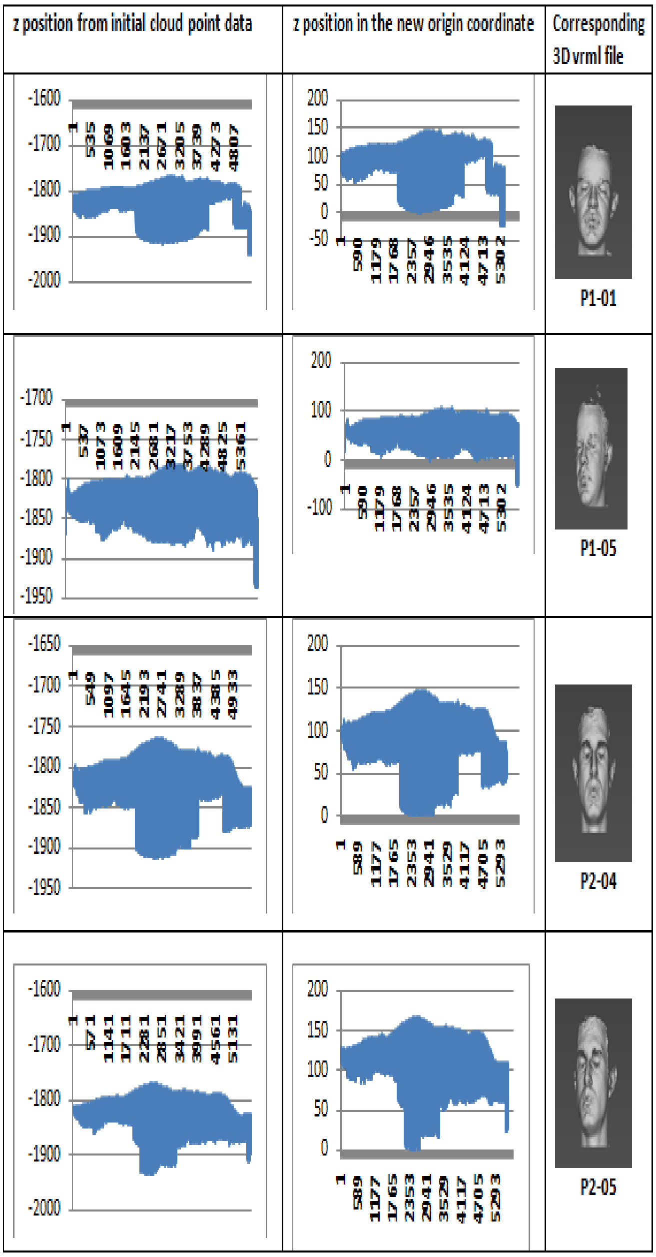

Fig 2: some samples of Z- coordinate vector in the original and in the new coordinate system

3. GAUSSIAN–HERMITE MOMENTS

As mentioned in the introduction section, moments and functions of moments have been widely used in domains of image analysis. Examples of moment-based feature descriptors include Cartesian geometrical moments, rotational moments, orthogonal moments, and complex moments. Among all kinds of moments, the geometric one is firstly introduced and has been used due to its explicit geometric meaning.

The direct description of moment invariants was first introduced by Hu. The major weakness of the Hu's theory is that it does not provide for a possibility of any generalization [13].

Orthogonal Moments like Legendre and Zernike were used to represent the image. These orthogonal moments and their inverse transforms have been used in the field of pattern representation, image analysis, and image reconstruction with some success. The difficulty in the use of moments is their high computational complexity, especially when a higher order of moments is used[14].

Gaussianl-Hermite Moments(GHM) were introduced by J. Shen[15] [16]

Given the Gaussian smoothing function g(x,σ):

$$g(x,\sigma)=(2\pi\sigma^2)^{-1/2}\exp(-x^2/2\sigma^2)$$

The n^{th} order smoothed Gaussian Hermite Moments of a signal S(x) is defined as:

$$GHM_n(x,S(x))=\int_{-\infty}^{+\infty} g(t,\sigma)H_n(t/\sigma)S(x+t)dt$$

With $H_n(t)$ is a scaled Hermite polynomial function of order n.defined as: $H_n(t/\sigma)=(-1)^n\exp(t^2)\dfrac{d^n\exp(-t^2)}{dt^n}$

The GHM_0 and GHM_1 can be calculated in the discret domain as follows:

$$GHM_0(x,S(x))=g(x,\sigma)*S(x)=\sum_{i=0}^{n} S(i)g(x-i)$$

$$GHM_1(x,S(x))=2\sigma\frac{d[g(x,\sigma)*S(x)]}{dx}=2\sigma\frac{d[g(x,\sigma)]}{dx}*S(x)$$

where * denotes the convolution operator.

The GHM_n can be recursively calculated for $n\geq 2$ as follows [11]:

$$GHM_n(x,S(x))=2(n-1)GHM_{n-2}(x,S(x))+2\sigma GHM_{n-1}(x,S(x))$$

GHM have many excellent performances, especially insensitive to noise. The parameter σ and the order of G-H Moments can be determined by experiments. Here we use GHM_0, GHM_1 and GHM_2 to analyze the shape variation and $\sigma = 0.2$.

4. THE RECOGNITION PROCESS

As mentioned in the previous section, we investigate GHM to get features to be used in the classification task. These features are then used as input of the classifier. We adopt back propagation neural network to do so. It is a multi-layer feed forward, supervised learning network based on gradient descent learning rule. we train the network to perform its ability to respond correctly to the input patterns that are used for training and its ability to provide good response to the input that are similar from the testing DB.

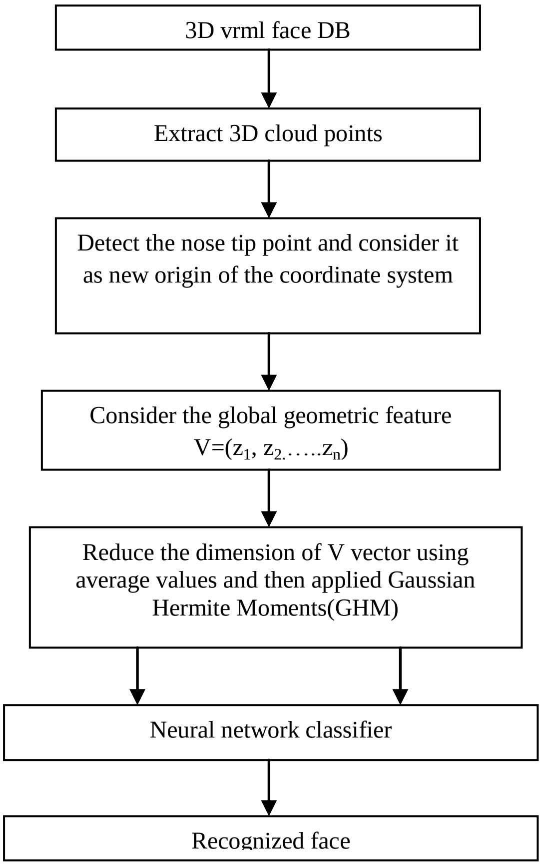

Fig3: The architecture of the proposed solution

5. EXPERIMENTAL RESULTS

5.1 Using GHM

The experiments were conducted and evaluated based on a set of 10 individuals from FRAV3D DB[17]. Data were acquired with a Minolta VIVID 700 scanner, which provides with not only texture information (2D image), but also a face model in range data format (2.5D image) and a VRML file (3D image). A total of 16 captures per person were taken in every session, with different poses and lighting conditions.

Label	**Type of image**
01 - 04	Frontal
05 - 06	Right turn 25º (respect to Y axis)
07 - 08	Left turn 5º (respect to Y axis)
09	Severe right turn (respect to Z axis)
10	Soft left turn (respect to Z axis)
11	Smiling face
12	Open mouth
13	Looking upwards (turn respect to X axis)
14	Looking downwards (turn respect to X axis)
15 - 16	Frontal view with lighting changes

Table1: description of the acquisition order

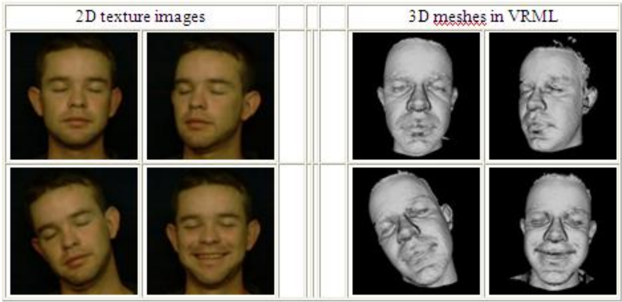

Fig 3: some example of 2d images and vrml files. Some samples from FRAV3D Database

Six samples (1,2,6,12,13,14) were used for training and the rest for test.

We train our neural network with the following setting: 100 inputs per pattern, 75 hidden neurons, 10 outputs neurons, and the error is set to 0.0001 for stopping condition.

Comparison between n=0, n=1 and n=2 and without GHM.

Results:

FRAV 3D	Using only z-coordinate	GHM 0	GHM 1	GHM 2
80 Samples	95%	95%	Not interesting	93%
160 Samples	46%	89%	Not interesting	84%

Table2: the rate of recognition

5.2 Using Distances and angles between anthropometric facial points

Craniofacial anthropometry is a technique used in physical anthropology for creating parametric models of human faces[18]. Over the years numerous anthropometric facial proportions have been proposed, and researchers have collected, recorded and analyzed their values on various human populations[19]. In this study, anthropometric facial points are used from Texas 3D Data base [20]. We choose seven fiducial points which are invariant to isometric deformations and benefit from the symmetry of the face.

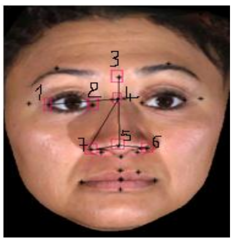

Fig4: Fiducial point location: P1:Left Outer Eye; P2: Left Inner Eye; P3: Head base point; P4: Upper nose point; P5: Nose Tip; P6: Right Nose Base; P7: Left Nose Base;

These fiducial points are manually located on the facial samples from the Texas 3D Face Recognition Database[20]. For the feature extractor vector, we extract ratio of distances and angles from selected fiducial point as illustrated in Fig 4. Features are extracted from those points as illustrated bellow. These features are then fed into BPNN for classification task.

X1= ang(P3,P4,P5);

X2= ang(P2,P4,P5);

X3= ang(P7,P4,P5);

X4= ang(P6,P5,P7);

X5=dist(P2,P5)/dist(P4,P5);

X6=dist(P6,P7)/dist(P4,P5);

X7=dist(P1,P4)/ dist(P4,P5);

X8=dist(P2,P4)/dist(P7,P5);

The experiments were conducted and evaluated based on several conditions from 10 sets of faces from 3D Texas DB, each person of the chosen persons have 23 different conditions: neutral, facial expression and illumination. Ten images were used for training and the rest for testing. The rate of recognition attends 82% for a data base composed by 230 samples.

We remark that results of the first method are more accurate than those of the second even if samples in the Frav3D DB incur more variations than those in Texas DB. We can deduce also that method using global information gives better results than local ones.

6. CONCLUSION

We present in this paper a 3D face recognition solution. 3D cloud points are first extracted from each sample in the DB and 1D feature vectors based on depth information are considered then Gaussian-Hermite Moments (GHM) are applied. The result features were used as input vectors of the Back Propagation neural network for the classification task. We compare the obtained results to results obtained when investigating the use of features composed of angle and distance measurement of manually selected 3D anthropometric facial fiducial points. Experiments show that results obtained when applying GHM are more effective.

7. REFERENCES

[1] Phillips, P.J., Scruggs, W.T., O'Toole, A.J., Flynn, P.J., Bowyer, K.W., Schott, C.L., Sharpe, M. 2007. FRVT 2006 and ICE 2006 Large-Scale Results, NISTIR 7408. National Institute of Standards and Technology.

[2] Jafri, R and Arabnia, R. "A Survey of Face Recognition Techniques", Journal of Information Processing Systems, Vol.5, No.2, 2009.

[3] Andrea, F., Michele, N., Riccio, D., Sabatino, G., "2D and 3D face recognition: A survey", Pattern Recognition Letters, Vol. 28, No. 14, 2007, 1885-1906.

[4] Pears,N., Heseltine,T., Romero,M., "From 3D Point Clouds to Pose-Normalised Depth Maps", Int J Comput Vis, 2010, 152-176.

[5] Wang,C., Niu,X., Lu,W., Gong,J., "A Hybrid Method to Build a Canonical Face Depth Map", International Journal of Digital Content Technology and its Applications, Vol.5, No. 5, May 2011.

[6] Alessandro Colombo, Claudio Cusano, Raimondo Schettini, "3D face detection using curvature analysis", Pattern Recognition Vol.39, No. 3, 2006, 444-455.

[7] Khalid,F., Lili, N. A., "3D Face Recognition Using Multiple Features for Local Depth Information"**,** IJCSNS International Journal of Computer Science and Network Security, Vol.9 No.1, 2009

[8] Gupta, S., Aggarwal, J. K., Markey, M.K., Bovik, A.C. 2007. 3D Face Recognition Founded on the Structural Diversity of Human Faces. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition CVPR '07.

[9] Bo Yang, Mo Dai, "Image analysis by Gaussian–Hermite moments", Signal Processing, 2011, 2290–2303.

[10] Jing YANG, Guohua PENG, "Subpixel Edge Location Based on Gaussian-Hermite Moments", Journal of Information & Computational Science, Vol.8,No.14, 2011, 3131–3140.

[11] Youfu Wu, Jun Shen, "Properties of Orthogonal Gaussian-Hermite Moments and Their Applications", EURASIP Journal on Applied Signal Processing, 2005, 588–599.

[12] Xu, C., Wang, Y., Tan, T., Quan, L. 2004. Automatic 3D face recognition combining global geometric features with local shape variation information. In the Proceedings of the Sixth Int. Conf. on Automated Face and Gesture Recognition, 308–313.

[13] Flusser, J. 2006. Moment Invariants in Image Analysis, Ttransactions on engineering, computing and technology.

[14] Aarif, T., Shaaban,Z., Krekor,L., baba, A., "object classification via geometrical, zernike and legendre moments", Journal of Theoretical and Applied Information Technology, Vol. 7, No. 1, 2009, 31 -37.

[15] Shen, J. 1997. Orthogonal Gaussian-Hermite Moments for Image Characterization. In Proceedings of Intelligent Robots and Computer Vision XVI: Algorithms Techniques, Active Vision, and Materials Handling, 224-233.

[16] Shen, J.; Shen, W. & Shen, D., "On Geometric and orthogonal moments". International Journal of Pattern Recognition and Artificial Intelligence, Vol.14, No.7, 2000, 875-894.

[17] http://frav.escet.urjc.es/databases/FRAV3D/

[18] Farkas, LG and Munro. 1987 Anthropometric Facial Proportions in Medicine. Charles C Thomas: Springfield.

[19] Y. Wang, C. Chua, and Y. Ho. Facial feature detection and face recognition from 2d and 3d images. Pattern Recognition Letters, Vol.23, No.10, 2002, 1191–1202.

[20] Gupta, S., Castleman, K. R., Markey, M. K. & Bovik. 2010. Texas 3d face recognition database. In Image analysis and interpretation, IEEE Southwest Symposium on, Austin, TX.