3D Gabor-Edge Filters Applied to Face Depth Images

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***Abstract*—This manuscript introduces a novel 3D face authentication system inspired from the advantageous capacities of Gabor-Edge filters. The approach studies 3D face difficulties such as expression variety, different rotations and exposure to illuminations. The proposed systems starts by preprocessing the 3D face images to resolve acquisition problems. Then, a filtering process is performed by implanting our 3D Gabor-Edge technique extended based on the classic 3D Gabor masks. The next step is to achieve the classification of facial features from the edge saliency by the artificial Neural Network Classifier (NNC). The evaluation of the adopted system is achieved by exporting common datasets from GavabDB database. Experimental results are reported to prove the high accuracy rates of our method compared to the recent researches in the same biometric field.**

Keywords—face authentication; Gabor filtering; 3D images; saliency;

I. INTRODUCTION

Recently, automatic 3D face authentication has attracted the attention of researchers due to the impressive results achieved using computer programs [1-5]. Despite all the progress, machine intelligence is always sensitive and require high survey due to the complexity of the task that we seek to automate, especially with biometric applications.

The way of representing 3D face images is a very important factor that strongly influences the performance of the adopted method. In practice, 3D images are divided in three categories, which are point cloud images, depth maps and mesh data. This means that working on facial data needs first to know the characteristics of the appropriate data. It is verified that manipulating 3D mesh and depth maps is much more efficient than 3D point clouds because of the connected structure of information contained. Furthermore, mesh images are largely integrated in 3D face detection. However, they present two major disadvantages, which are the similarity between the facial maps of the different subjects and the small amount of the training samples because of the high cost of their scanning and storage. For sure, it is a waste of time to compute the recognition procedure through tens of thousands of vertices and facets with irrelevant information. For this reason, achieving face authentication from depth maps is a good solution to reduce the complexity cost and permits to exploit both intensity and depth characteristics, which is beneficial for feature extraction and classification.

Several methods of face authentication have been proposed in the recent years, following two main axes: identification from 2D and 3D images and identification from video clips [3-4]. For example, Chiraz and Paul [6] studied the effect of combining shape and texture information by exporting depth and texture information from 3D face images. The method also designed a classification pattern using Fisherfaces in order to apply 3D matching. Later, Berk et al. [7] used only shape scans and classified them by introducing Thin Plate Spline (TPS) warping. Another approach presented by Yuki and Takeshi [8] had geometrically normalized volumetric images in a manner to get intensity representations permitting to extract local landmarks.

In pattern and biometric applications, a key parameter is the nature of the "visual characteristics" used. These characteristics serve both for the construction of models and for the identification of images. In this context, feature extraction based approaches manipulate 3D images by decomposing the structure of the surface into regions of interest to allow locating the main key points. As it can be reported in the work of Sha et al. [9], two types of landmark extraction techniques were applied: Surface Curvature Features (SCF) and Geometrically Localized Features (GLF). Both methods were targeted at the most pertinent features characterizing the human face such as the nose topology, the eyes curvatures and the mouth lines. Also, Tang et al. [10] established a curvature based technique by implanting Asymptotic Cones in curvy zones. Their approach has exploited the concave and the convex locations in the face in order to build similarity vectors between the tested images and the trained ones.

As a manner of fact, multiple techniques have appeared to resolve 3D face scanning issues such as the variation of the pose and the expressions [11-12]. In addition to these acquisition difficulties, illumination variety and partial occlusions are also serious challenges in the domain of biometric tasks. For this to be treated, several researchers have employed classic Gabor filters that confirmed an impressing capacity in the face authentication field. Nanni et al. [13] proposed weighted Sub-Gabor masks that extract pertinent data from face images and provide it for a Genetic Algorithm based classifier. Also, Tie and Ling [14] established a 3D visual Gabor bank and tested it on difficult expressions like disgust, surprise and fear. The method verified an accuracy score about 77.57%.

In the same spirit, Shen and Bai [15] presented a full review describing the benefits and limitations of these face-simulating filters. The review focused on the details of the conventional form of Gabor masks and reported a comparaision between the most recent researches tested on multiple common databases.

In this manuscript, we introduce a face authentication paradigm based on extracting 3D Gabor-Edge Features (3D-GEF) from depth maps. First, section 1 details the proposed method and presents the main contribution. In section 2, we provide the experimental results on GavabDB database. In section 3, conclusions and perspectives are introduced.

II. Proposed 3D Face Authentication System

A. *Proposed 3D Face authentication system*

In this work, a new 3D face authentication paradigm is presented using a novel extension of the classic 3D Gabor wavelet library. The method investigates feature extraction of the pertinent points in the line and edge zones of a human face. As it can be seen, Fig.1 presents the adopted recognition system. It starts with a preprocessing stage, then, a landmark extraction stage is achieved via the proposed Gabor-Edge filters. Finally, the classification process is performed with the supervised NNC technique.

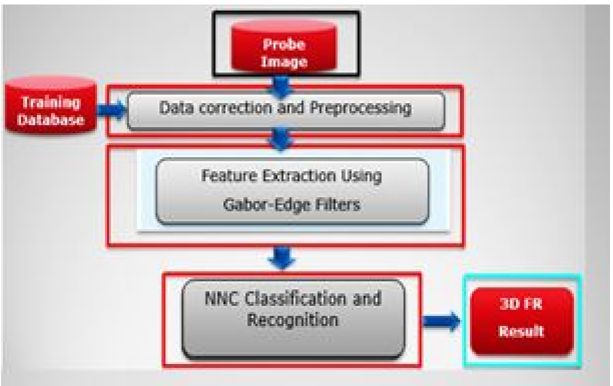

Fig. 1. Pipeline of the adopted 3D face authentication system.

Thus, the 3D original images are exposed to preliminary processing. The urgent need to exploit all required data from the 3D models encourages to correct them from high noises and frequency spikes by applying a cascade of median filters. Then, the surface of each image is examined in order to detect holes and fill them through Laplacian interpolations. This operation permits to preserve the surface connectivity and correct data deficiency.

Once the preprocessing steps are achieved, the depth images are normalized and cropped in order to extract only the face zone, which is extremely important in a manner to lower computational time. The proposed Gabor-Edge filtering provide the NNC classifier with pertinent feature vectors used to separate the "recognized faces" from the "non-recognized faces".

B. *Feature Extraction Using Gabor-Edge Filtering*

Recently, feature extraction using the usual Gabor masks has rapidly emerged in the pattern recognition field [13-14]. Principally, these wavelets permits to simulate the human face and extract the majority of saliency from its global structure. It is an automatic and intelligent tool to imitate visual perception in a manner to detect the major features that determine whether a face is recognized.

Inspired by the classic Gabor filters that are constructed using 8 orientations and 5 different scales (as demonstrated in Fig. 2), we build our Gabor-Edge wavelets in the 3D domain.

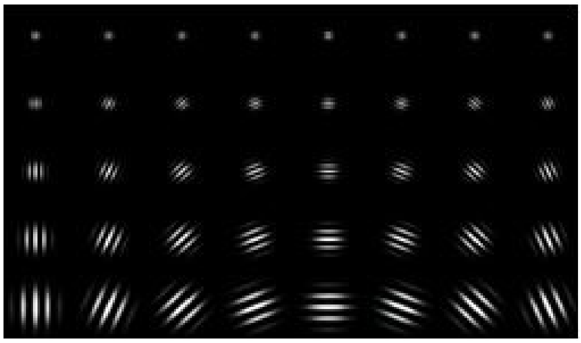

Fig. 2. Representation of 2D Gabor wavelets under 8 orientations and 5 scales.

By modulating the product of a sinusoid wave using a Gaussian window, we can construct a Gabor function defined as:

$$T_{\alpha,\beta,\gamma}(x,y,z) = N \times E(x',y',z') \times P(x,y,z) \qquad (1)$$

where (x,y,z) are the coordinates of an arbitrary point in the 3D space and E the Gaussian envelope as:

$$E(x',y',z') = \exp\left(-\tfrac{1}{2}(X'^2 + Y'^2 + Z'^2)\right) \qquad (2)$$

and $X' = \dfrac{x'}{\sigma_{x'}}, Y' = \dfrac{y'}{\sigma_{y'}}, Z' = \dfrac{z'}{\sigma_{z'}}$.

The normalization factor $N = (1/(2\pi)^{3/2}\sigma_x'\sigma_y'\sigma_z')$ depends on the Gaussian width parameters $\sigma_x', \sigma_y', \sigma_z'$ and P is defined as:

$$P(x,y,z) = \exp(-j2\pi(F_1 x + F_2 y + F_3 z)) \qquad (3)$$

F_1, F_2 and F_3 are the frequencies of the complex sinusoid in the 3D domain defined as:

$$\begin{cases} F_1 = \alpha \sin\beta \sin\gamma \\ F_2 = \alpha \sin\beta \cos\gamma \\ F_3 = \alpha \cos\beta \end{cases} \quad (4)$$

The rotation matrix M permits to transform E in order to coincide with the defined orientation of the complex sinusoid as:

$$(x', y', z')^T = M \times (x, y, z)^T \quad (5)$$

and:

$$M = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos\beta & -\sin\beta \\ 0 & \sin\beta & \cos\beta \end{pmatrix} \times \begin{pmatrix} \cos\gamma & -\sin\gamma & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (6)$$

where $\alpha = \sqrt{(F_1^2 + F_2^2 + F_3^2}$, $0 \le \beta \le \pi$ and $0 \le \gamma \le \pi$

By varying the rotation parameters, 3D Gabor filers $T_{\alpha,\beta,\gamma}(x, y, z)$ are constructed (Fig. 3).

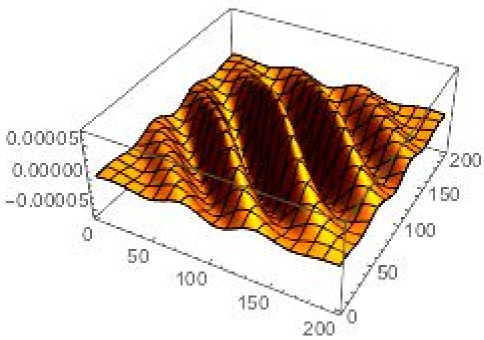

Fig. 3. Example of a 3D Gabor wavelet.

Generally, 3D Gabor wavelets are focusing on the most acute components in the image. The set of responses of the Gabor filters forms a vector transmitted at the input to the classification system.

C. Gabor-Edge Filtering

In the present application, facial features participate in the act of communication between human beings: for example, the visualization of the lips and their movement makes it possible to improve the comprehension of a message in a noisy environment. The purpose from performing the Gabor-Edge filtering is to obtain an automatic and precise extraction of the contours of the facial features. The edges in a 3D image are measured by applying the Gabor-Edge T_{Edge} with the modified Gaussian envelope as:

$$E(x', y', z') = \exp\left(-\tfrac{1}{2}(X'^2 + \phi^2 Y'^2 + Z'^2)\right) \quad (7)$$

ϕ is the spatial aspect ratio that permits to define the intensity of the edge in the considered face image. The complex sinusoid wave is also designed using the wavelength ψ as:

$$P(x, y, z) = \cos(2\pi \frac{X}{\psi} + \theta) \quad (8)$$

The phase offset $\theta \in \{0, \pi\}$. When convolving the Gabor-Edge filters with the 3D depth image, we obtain Gabor-Edge representations that describe the saliency located in the mouth zone, the eyes lines and the nose structure (Fig. 4).

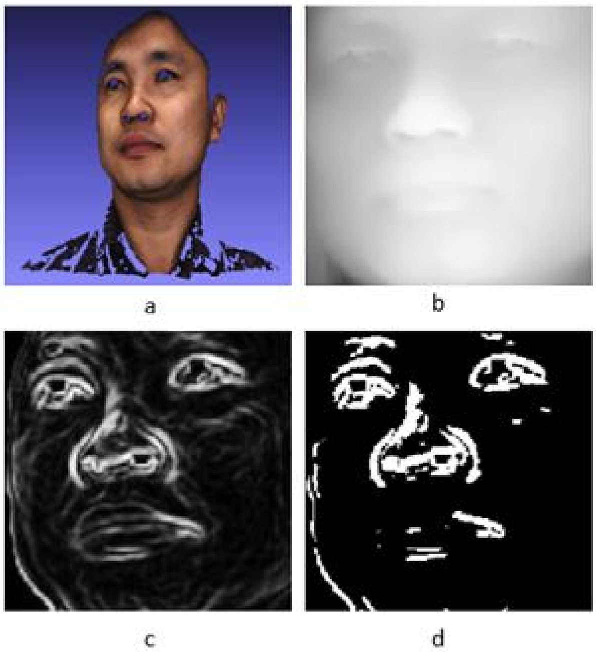

Fig. 4. An example of Gabor-Edge filtering (a) 3D face image (b) Depth image (c) Gabor-Edge filtering (d) The result from thresholding the edge saliency.

D. Artificial Neural Network Classifier

In this work, we discuss the classification of discriminant facial features using the supervised technique NNC. Our objective is to group the facial biometric characteristics in a reduced subspace in order to recognize those characteristics corresponding to the same class.

In the present biometric application, the most fitting neural networks is the Multi-Layer Perceptron (MLP) which consists of a succession of layers, completely or partially interconnected [16]. The NNC classification based on the MLPs layers permits to classify progressively the discriminant features provided by the Gabor-Edge representations of each test image. The automatic learning algorithm aims principally to transmit the expected result to all the MLPs, each processing a unit. When a face is the subject of the automatic learning achieved by the NNC process , the first step is to transmit to the local MLP network the features located in the eye zone, the mouth and the nose because they are the most salient regions of the face structure. Once the feature vectors are classified, the system returns the recognized face with an authentication indication and rejects the images that do not belong to the gallery set.

III. Results and Analysis

In this section, we focus on validating the efficiency of the Gabor-Edge filtering technique in achieving 3D face recognition. The evaluation process is accomplished by selecting a common database of 3D face images and compare the experimental results with existing methods.

We present the experimental results carried on a collection of images selected from the GavabDB database (Fig. 5). It is a common gallery of face images established by the scan of 61 individuals in different sessions. Each individual is represented with nine images under a variety of poses such as the head turned to the right and to the left, the eyes looking to the floor, etc. Also, the collection contains many facial expressions such as anger, terror, disgust, smiling and laughter. For this reason, GavabDB represents a solid database that permits to evaluate the proposed algorithm performance under various conditions.

Thus, two sub-collections are constructed based on the 427 images: the first one is the probe sub-collection containing the images to be recognized. The remaining images are gathered in the training sub-collection. When an image is tested, it is automatically compared to the images existing in the training sub-collection. The similarities are detected from the Gabor-Edge representations using the NNC classifier.

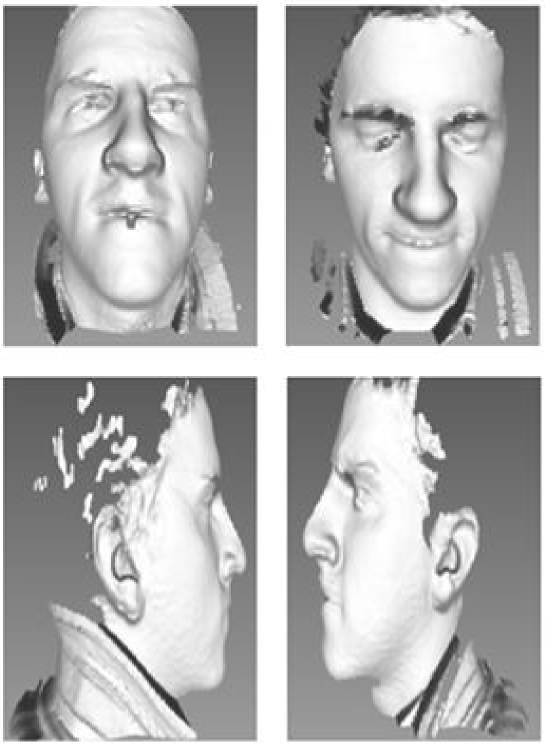

Fig. 5. Example of 3D images from the GavabDB collection.

In order to verify the efficiency of the present algorithm, we define the Accuracy Rate (AR) which is the evaluation score as

$$AR = \frac{Number\ of\ identified\ subjects}{Total\ number\ of\ the\ subjects} \quad (9)$$

TABLE I. Accuracy Rates Under Various Scanning Conditions

	Number of subjects (test sub-population)	AR (%)
Frontal neutral poses	61	98.36%
Pose variety	55	98.33%
Expressing smile	20	95%
Strong illumination	40	97.5%
Occlusions	10	90%

Table I reports the ARs resulting from applying the adopted face recognition system under several environmental situations including facial expression and rotation variety. The results validates high recognition rates even on severe conditions. The reason behind the sensible reduction of the ARs comparing to the frontal neutral image face is the decrease of the facial features number. Even of this data reduction, Gabor-Edge filtering has confirmed its robustness towards intense variations.

TABLE II. Comparaision of Accuracy Rates with Other Methods

Reference	Method	AR
Panchal and Shah. [17]	PCA + Euclidean distance	74.89%
Ansari et al. [18]	Global alignement + 3D matching	90.3 %
Yan-Ning et al. [19]	Local Region Map (LRM)	93.1%
Peng and Limming [20]	LRM + Facial Structural Angle (FSA)	93%
Proposed Method	Gabor-Edge filters	98.36%

In addition to that, in order to evaluate the performance of the present approach, it is important to compare its results with existing techniques working on the same GavabDB database. For example, Panchal and Shah. [17] applied Euler Angle Method on 3D face images. Their technique is based on PCA feature extraction and Euclidean distance classification. In addition, Ansari at al. [18] achieved 3D face recognition using range images after performing mesh alignment. The experimental ARs are reported in Table II with those of other recent methods [19-20]. As it can be concluded from the stated results, our proposed 3D face recognition algorithm has achieved 98.36% which is the highest score comparing to the other approaches.

IV. Conclusion

In this work, a new solution to 3D face authentication is proposed based on the advantageous capacities of Gabor-Edge filtering. The method uses Gabor contour representations applied to 3D depth images in order to extract the most salient features located in the face lines and edges. The classification of the pertinent feature vectors is achieved using NNC classifier. Thus, the system performance is validated by conducting the algorithm on GavabDB database. Experimental results shows a robustness towards a variety of severe scanning conditions. The efficiency and solidness of Gabor-Edge facial recognition is also verified by comparing the results with those of other existing techniques.

As in the future work, our intention is to upgrade the performance of the proposed approach using a memetic optimization technique.

References

[1] K. Lin, X. Wang, X. Li and Y. Tan, “Self-adaptive morphable model based multi-view non-cooperative 3D face reconstruction,” 2014 IEEE Congress on Evolutionary Computation (CEC), Beijing, 2014, pp. 320-325.

[2] Y. Huang, Y. Fan, W. Liu and L. Wang, “3D human face modeling for facial animation using regional adaptation,” 2014 IEEE China Summit & International Conference on Signal and Information Processing (ChinaSIP), Xi'an, 2014, pp. 394-398.

[3] H. Tang, Y. Sun, B. Yin and Y. Ge, “Self-Adaptive 3D Face Recognition Based on Feature Division,” 2009 Fifth International Conference on Image and Graphics, Xian, Shanxi, 2009, pp. 885-890.

[4] Z. Guo, Y. Zhang, Y. Xia, Z. Lin and D. Feng, “3D face representation and recognition by Intrinsic Shape Description Maps,” 2010 IEEE International Conference on Acoustics, Speech and Signal Processing, Dallas, TX, 2010, pp. 854-857.

[5] P. Bagchi, M. Nasipuri, D. Bhattacharjee and D. K. Basu, “A novel approach for nose tip detection using smoothing by weighted median filtering applied to 3D face images in variant poses,” International Conference on Pattern Recognition, Informatics and Medical Engineering, Salem, Tamilnadu, 2012, pp. 272-277.

[6] B. Chiraz and A.G. Paul, “Comparing and combining depth and texture cues for face recognition,” J. Im. and Vis. Comp. vol. 23, 2005, pp. 339-352.

[7] G. Berk, I. M. Okan and A. Lale, “3D shape-based face representation and feature extraction for face recognition,” J. Im. and Vis. Comp. vol. 24, 2006, pp. 857-869.

[8] O. Yuki and S. Takeshi, “Real-time face tracking and recognition by sparse eigentracker with associative mapping to 3D shape,” J. Im. and Vis. Comp. vol. 30, 2012, pp. 147-158.

[9] T. Sha, M. Song, J. Bu, C. Chun and T. Dacheng, “Feature level analysis for 3D facial expression recognition,” J. Neurocomputing, vol. 74, 2011, pp. 2135-2141.

[10] Y. Tang, X. Sun, D. Huang, J. M. Morvan, Y. Wang and L. Chen, "3D face recognition with asymptotic cones based principal curvatures," 2015 International Conference on Biometrics (ICB), Phuket, 2015, pp. 466-472.

[11] L. Yin, X. Wei, Y. Sun, J. Wang and M. J. Rosato, “A 3D facial expression database for facial behavior research,” 7th International Conference on Automatic Face and Gesture Recognition (FGR06), Southampton, 2006, pp. 211-216.

[12] P. S. Hiremath and M. Hiremath, “3D face recognition based on depth and ntensity Gabor features using symbolic PCA and AdaBoost,” Int. J. of Sig. Proc. Im. Proc. and Patt. Rec. Vol. 6, 2013, pp. 1-12.

[13] L. Nanni and D. Maio, “Weighted Sub-Gabor for face recognition,” J. Im. and Vis. Comp. vol. 28, 2007, pp. 487-492.

[14] Y. Tie and G. Ling, “Human emotional state recognition using real 3D visual features from Gabor library,” J. Patt. Rec. vol. 46, 2013, pp. 529-538.

[15] L. Shen and L. Bai, “A review on Gabor wavelets for face recognition,” J. Patt. Anal. App. vol. 9, 2006, pp. 273-292.

[16] H. Boughrara, M. Chtourou and C. B. Amar, “MLP neural network based face recognition system using constructive training algorithm,” 2012 International Conference on Multimedia Computing and Systems, Tangier, 2012, pp. 233-238.

[17] K. Panchal and H. shah, “3D face recognition based on pose correction using euler angle method,” 2013 International Conference on Machine Intelligence and Research Advancement, Katra, December 2013, pp. 467-471.

[18] Ansari, M. Abdel-Mottaleb and M. H. Mahoor, “3D Face Mesh Modeling from Range Images for 3D Face Recognition," 2007 IEEE International Conference on Image Processing, San Antonio, TX, 2007, pp. 509-512.

[19] Z. Yan-Ning, G. Zhe, X. Yong, L. Zeng-Gang, D.F. David, “2D representation of facial surfaces for multi-pose 3D face recognition,” Pattern Recognit. Lett. vol. 33, 2012, pp. 530-536.

[20] G. Peng and Z. Limming, “3D face recognition based on facial structural angle and local region map,” 2008 IEEE International Conference on Multimedia and Expo, Hannover, 2008, pp. 41-44.