Region Based 3D Face Recognition

Reji R
Research Scholar,
School of Computer Sciences,
Mahatma Gandhi University, Kottayam,
Kerala , India.
reji.r@saintgits.org

Dr.P.SojanLal
Principal,
Mar-Baselious Institute of Technology & Science,
Kothamangalam, Kerala, India.
sojanlal@gmail.com

Abstract— **This paper focuses on a region based methodology for expression in sensitive 3D face recognition process. Considering facial regions that are comparatively unchanging during expressions, results shows that using fifteen sub regions on the face can attain high 3D face recognition. We use a modified face recognition algorithm along with hierarchical contour based image registration for finding the similarity score. Our method operates in two modes: verification mode and confirmation mode. Crop 100 mm of frontal face region, apply preprocessing and automatically detect nose tip, translate the face image to origin and crop fifteen sub regions. The cropped sub regions are defined by cuboids which occupy more volumetric data, Nose Tip is the most projecting point of the face with the highest value along Z-axis so consider it as origin. The modified face recognition algorithm reduces the effects caused by facial expressions and artifacts. Finally a Hierarchical contour based image registration technique is applied which yields better results. The approach is applied on Bosphorus 3D datasets and achieved a verification rate of 95.3% at 0.1% false acceptance rate. In the identification scenario 99.3% rank one recognition is achieved.**

Keywords— Biometrics; MFRA; Rank based Score; Contour based image registration; 3D face recognition.

I. INTRODUCTION

The term biometrics refers to identification of individuals on the basis of measuring physiological and behavioral attributes. Face recognition is the most natural unintrusive and robust of all the biometric techniques available. Face is considered as one of the most attractive biometric. The use of biometrics for security purposes is increasing day by day. A variety of 2D and 3D biometrics are available now. Earlier works in 3D facial recognition emerged in the end of 1980's. 3D face recognition has become popular in high security applications. It is a solution to the poor performance of facial recognition algorithms due to pose variation, illumination and expression. Expensive data capturing and computational complexity is a major limitation of 3D face recognition scenario. Face Recognition Grand Challenge 2.0 face database is one of the common dataset used for experimenting on 3D face biometrics[1]. The main aim of FRGC program was to increase the verification rate to 98% at 0.1% fixed false acceptance rate.

Numerous algorithms are proposed to address the different aspects of facial recognition process. There arises a need to analyze and evaluate the performance of different algorithms. Based on the performance in different datasets, improved algorithms are evolved. The GBU challenge problem [2] gives highlights to the fact that even though the effect of the most known elements are eliminated there can be variations in the performance of different partitions of data. Advanced studies shows that the quality of the face images comes in the form of pairs [3]. It is noted that the difference in the two images is the core factor that affects the similarity measure rather than the individual quality of the compared image considered alone.

Gaurav et.al[4] investigates the face image characterization, Image specific properties are more generic characterization of image that require no analysis in face images. But face specific characterization play a vital role in quantifying facial properties. In our work we are concentrating on the face specific characterization. 3D face recognition algorithms are classified as global based, region based and hybrid based algorithms[5].These categorizations are based on the modality. Global recognition algorithm extracts and analyze the core features from the entire face and is more susceptible to facial expressions. This opens way for local region based algorithms; in which features are extracted from regions that are less susceptible to facial expressions. In Hybrid based algorithm a combination of both global features and local features are used. Modified face recognition algorithm is a local region based algorithm. The Main operation of most face recognition system is divided into two categories, verification and identification. In verification the system validates the individual identity whether he/she claims to be but in identification the system recognize the person by searching the entire database. So verification is a 1:1 Process and identification is a 1: N process. The main challenges in any face recognition scenario are expressions, pose and occlusions. In this paper we are concentrating with identification and our focus is on expression insensitive 3D face recognition. This paper extends the work in [6] by reducing the number of regions to 15, by considering the fact that there are areas on the face that remain relatively unchangeable in the presence of facial expressions. Our method crop 15 sub regions from the frontal face region of 100mm diameter and find similarity between probe and gallery. Modified Face Recognition Algorithm with an additional hierarchical registering technique is used to calculate the similarity measure. Score based approach followed by the ranking enhance the overall performance even in the presence of facial expressions. Experiments are done on the Bosphorus 3D datasets [7] which

978-1-5090-6621-6/17/$31.00 ©2017 IEEE

is unique in three aspects namely, rich source of expressions, systematic head pose variation and a variety of facial occlusions.

The Sections of the paper is as follows. Section II gives an insight into the related work . In Section III we provide the details of our proposed system. Section IV presents experiments along with discussions and Section V provides conclusions.

II. RELATED WORK AND OVERVIEW

A detailed survey of the techniques used in face recognition using 3D data is given in [8, 9]. Chang et al. [10] divides the 3D face into sub regions, these regions are located in and around the nose. The sub regions include a circular, elliptical nose region or a region composed of the nose itself. These sub regions are used for comparison instead of the whole frontal face region. ICP algorithm is used for image comparison and results are reported on the superset of FRGC v2 dataset. They reports results of 97.1% and 87.1 % rank one recognition rate on neutral probe to neutral gallery and neutral probe to non neutral gallery. Finally the Author concludes that performance can further be gained by increasing the number of sub regions.

Faltemier et al.[11] presented a region based strategy by dividing the frontal face region into 28 sub region and matched independently. Borda count and consensus voting method was employed to obtain better performance. They reported a rank one recognition of 97.2% and verification rate of 93.2% at an FAR of 0.1%. The authors extends their work later by increasing the number of sub regions to 38. Results are reported on FRGC v2 dataset and stated that the top level 3D face recognition can be obtained from 28 sub regions .

In our previous work we employed a region based approach by splitting the frontal face region into 48 sub regions. Sub regions are divided based on the nose tip as origin. The nose tip is identified manually. Feature level fusion is applied using Euclidean distance as measure, reported 97.1% rank one recognition and verification rate of 93.7% on a third party datasets.

Zhong et al. [12] divides the frontal face into two regions, the above face region and the below face region. The above face region without the mouth is used for experimentation. Features are extracted using Gabor filters. The final result is obtained by applying K-means clustering techniques and nearest neighbor classifier.

Lu et al. [13] employed 598 2.5- D probe model of different pose and facial expressions, and is matched to a gallery of 200 faces. They are making use of the full 3D image of the subjects. ICP, LDA algorithms are applied and reported a rank one recognition of 90%.

Cook et al. [14] used Log -Gabor templates on range images to deal with expression variation. The face is divided into 147 sub regions and the size of the Log –Gabor filter responses is reduced by the application of PCA. Results are reported on FRGC v2 datasets with recognition performance of 94.63%.

Mian et al.[15] automatically segmented the 3D face into different sub regions. For face recognition a spherical representation of face, SIFT transform and a modified ICP algorithm is used.

Queirolo et al.[16] presented an approach called Simulated annealing along with surface interpenetration measure. They are using the whole frontal face region and identified 6 control points. Results are reported on the FRGC v2 datasets. Four different SIM values that correspond to four different face region is combined for final recognition results.

Anuar et al. [17] discusses the relevance of nose tip detection in face analysis. Nose region is the most projecting part of a normal face. Convex points of the face surface along with morphological approaches are applied to get nose tip region candidates. The highest point density is analyzed and a signature is generated for evaluation.

Drira et al.[18] propose a novel geometric frame work for analyzing 3D faces. Facial surfaces were represented by radial curves and use an elastic shape analysis to develop a frame work for analyzing face of full facial surface.

Lie et al. [19] presents a 3D face recognition approach based on low level geometric features collected from the eyes, forehead and nose regions.These subregions are comparatively unchangeable in the presence of facial expressions. A region based histogram is used to represent the 3D face. A fusion of feature level and score level is applied for evaluation.

III. PROPOSED SYSTEM

The proposed system employs 5 steps, 1) Data preprocessing 2) Nose tip detection 3) Sub region creation and alignment to gallery 4) Modified face recognition algorithm.5) Hierarchical Contour based image registration. This system is having two modes of operations: the verification mode and the confirmation mode. In the verification mode we are finding whether there is a match to the probe image and the gallery. Once there is a match then we are moving to the next mode, i.e. the confirmation mode. The verification mode is having two phases namely training phase and test phase and the confirmation mode is making use of a hierarchical contour based image registration approach. In training phase preprocessing, nose tip detection, sub region generation and alignment of sub region to gallery occurs.

A. Preprocessing

3D information requires preprocessing depending on the sensor used and the acquisition method employed. 3D scans may have noise and holes. This led to problems while matching with the probe to gallery. Fill the holes and missing points with interpolation techniques. In this approach we are filling the holes, artifacts and noise by applying Moving least square surface reconstruction method along with polynomial interpolation reconstruction algorithm. Initially we are experimenting with a third party data set, fig 2. In this case the weight function of the MLS is very crucial.

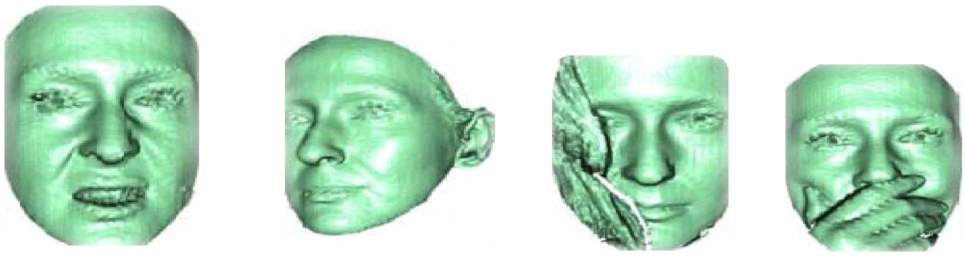

Fig. 1. [7] Major Challenges in 3D face recognition.

B. Nose Tip Detection

There are areas on the face that remains relatively consistent in the presence of expressions. Cropping the fifteen regions from the frontal face based on the probe list need to identify an origin. Since from literature [17] nose is the highest projecting region along the z axis. We are considering nose tip as the origin. This algorithm has mainly three functionalities. Identify the Nose area; figure out the nose tip candidates and finally nose tip detection. Curvature based shape descriptor is used to identify the nose area

Nose tip Detection Algorithm:

Step 1: Input the cropped image

Step2: Identify the salient point.

Step3: Apply the banana transform and response is calculated.

Step4: Based on the strong response the nose area is identified.

Step5: Analysis of the variance is used for finding the nose tip candidates.

Step6: Range down the nose tip candidates using statistical approaches.

Step7: The strongest Response is the nose tip.

C. Sub region Generation and Alignment to gallery

Our interest is in the frontal face region. So 100 mm of frontal face is enough for generating the sub regions and it contain the most invariant identifier such as the eyes, nose and the mouth. With nose tip as origin 15 sub regions are cropped from the frontal face. We are generating 15 cuboids rather than 15 circular regions because the volumetric data is more in cuboids than a circle, fig 3. The radius is experimentally chosen in such a way that at least one portion of the identifier is included in each sub region. Once the sub regions are generated then align it to gallery. When a probe image is obtained then the comparisons occurs in the gallery.

The next phase is the test phase, once a probe image is obtained it is smoothed and nose tip is identified. Now comparison occurs between the probe and the gallery. A variant ICP algorithm is used to calculate the match score. If the match scores is greater than or equal to threshold value, match occurs otherwise no match. Choosing the threshold value is so crucial. Once a match occurs apply the confirmation mode. In this mode rank based score is calculated. The probe image that matches the highest rank (Rank1) gallery image is identified.

Apply Hierarchical Contour based image registration technique to find the similarity. Divide the probe and the rank I matched image into 4 regions as shown in fig 4, upper head region and lower face region. In the contour of each region identify control points. In this approach one region is analyzed at each level of the hierarchy. Successive regions are taken only if the score of the previous one was not enough to a match. Contours are general descriptions in the image and it provides more geometric information. Contour segments are taken from the regions of the probe; Rank1 gallery image and a set of points are identified. Contour matching has three steps; matching of contour points, initial matching of contours and final matching of contour. In the first step a correspondence between contour points are established. In the next step pairs of contour points are identified from regions of the probe and gallery image. Next the final correspondence between the contour points of the two images is identified. Affine transform is applied and the similarity measure is calculated

IV. EXPERIMENTAL MATERIALS AND RESULTS

A. Bosphorus 3D Datasets

The Bosphorus dataset is suitable for 3D face analysis. It is identical in three major things, rich source of facial expressions, systematic variation in head poses and variety of facial occlusions. Data is obtained using structured three dimensional systems. The sensor has 0.33, 0.33 and 0.44 mm sensitivity in all dimensions. This is multi expression, pose data base. In Bosphorus dataset, two types of facial expressions are available, facial action units and emotional expression that are typically occurring in our real life. All the texture images are of good resolution with correct and proper illuminations. The data set contains 105 subjects having various poses, facial expressions and occlusion conditions. Most of the subjects are in the age between 25 and 35.There is 45 women and 60 men in total.

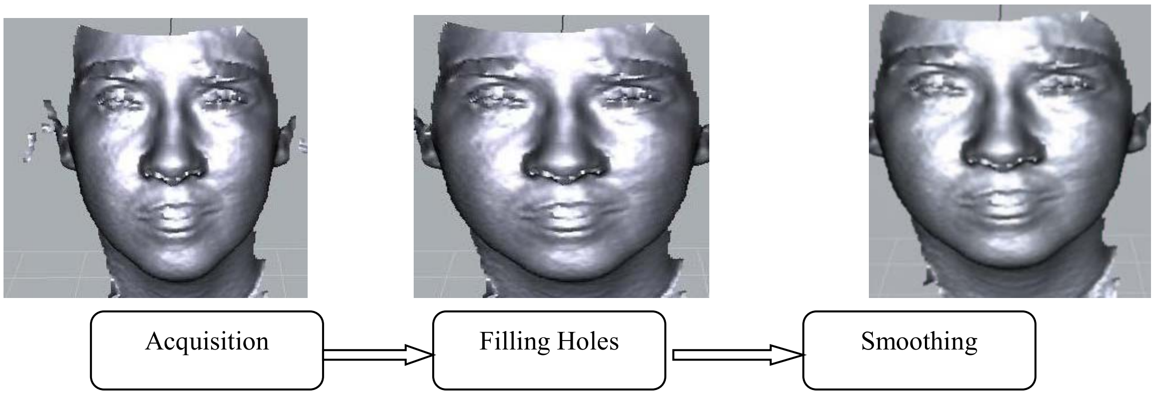

Fig. 2. Preprocessing

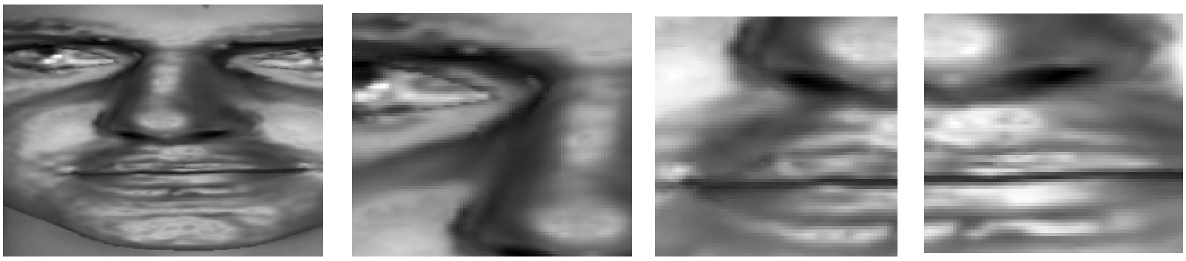

Fig. 3. Sub Regions

The subjects are of Caucasian origin, eighteen men had moustache or beard and fifteen other had short facial hair. Fatemier et.al [11] is making use of 28 sub regions on the face to achieve top level 3D face recognition. They extend their work to 38 sub regions and obtain a verification rate of 93.2%. In our previous work [6] we are taking 48 sub regions on the face and reported a verification rate of 93.7% at a FAR of 0.1% on a third party dataset.

Initially experiments are all done on neutral images and verification rate is calculated. Next case we consider expressions for that one neutral image and its non neutral image is tested .We consider only a few basic expressions such as happiness, surprise, fear, sadness, anger and disgust. The verification result is shown in table 1. In this paper we employ the experiments in two scenarios: verification and identification. In the verification scenario our aim is to answer if a person is who he or she claims to be. We are calculating the verification rate at 0.1% false acceptance rate.

The modified face recognition algorithm uses 15 sub regions and achieves a verification rate of 95.3% at a FAR of 0.1% as shown in fig 5. Each face from the probe is compared against a gallery, score is calculated and the result is compared with a threshold. In the identification scenario our aim is to prove who the person is to be. Identification rate can be measured by calculating the rank one recognition. Each face in the probe is compared against all gallery set. Rank based score is taken as a measure and hierarchical contour based image registration is applied for confirmation. Table 2 shows the execution time of the Modified face recognition algorithm in verification and confirmation mode. From preprocessing to hierarchical image registration technique the process takes less than 12 Seconds on a 2.40 GHz Intel Core i3 Processor with 4 GB of memory. This suggests that a feasible execution time may be achieved for use at critical security applications.

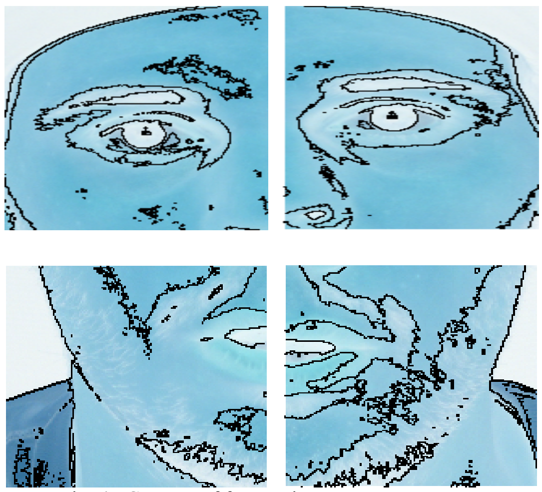

Fig. 4. Contour of face region

TABLE 1. VERIFICATION RESULT

<table>
<tr><th>Authors</th><th>Dataset</th><th>Expressions</th><th>VR at 0.1%FAR</th><th>Our 48 region Approach on a third party dataset (Basic expressions) VR at 0.1%FAR</th></tr>
<tr><td>Mian et.al[15]</td><td>FRGC v2</td><td>All Expressions Vs All Expressions</td><td>86.6%</td><td rowspan="4">93.7%</td></tr>
<tr><td>Cook et.al[14]</td><td>FRGC v2</td><td>All Expressions Vs All Expressions</td><td>92.31%</td></tr>
<tr><td>Maurer et.al[20]</td><td>FRGC v2</td><td>All Expressions Vs All Expressions</td><td>87.01%</td></tr>
<tr><td>Fatimier et.al[11]</td><td>FRGC v2</td><td>All Expressions Vs All Expressions</td><td>93.2%</td></tr>
</table>

TABLE 2. RUNNING TIME OF MFRA

Mode	Step	Time(s)
Verification	Data Preprocessing	**4.54**
	Matching	**1.94**
Confirmation	Registration	**5.12**

TABLE 3. VERIFICATION RATE

Paper	No : of regions	Verification rate at 0.1%FAR
Fatemier et.al[11]	28	93.2%
Fatemier et.al[11]	38	93.2%
Reji et.al[6]	48	93.7%

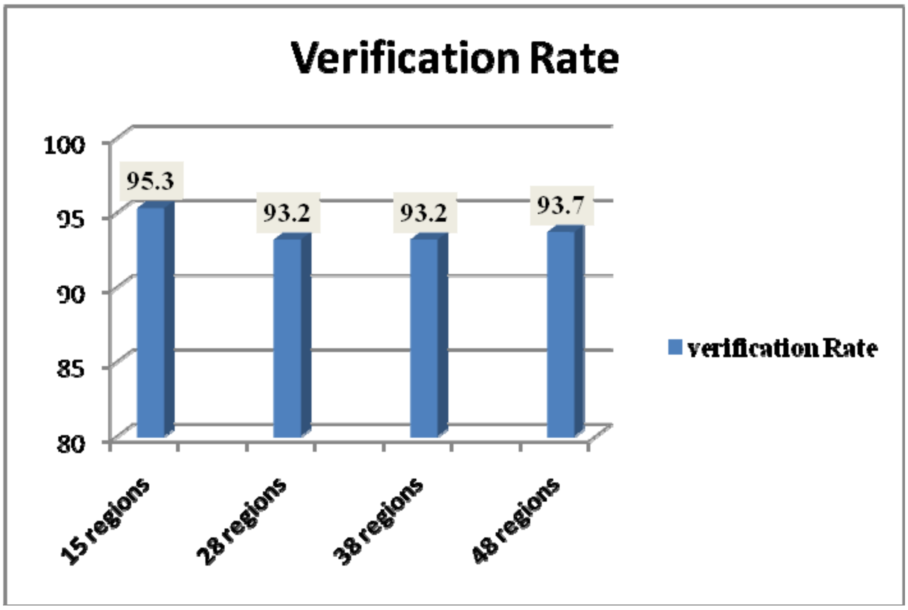

Fig.5. Verification Rate

V. CONCLUSION

We have presented a region based 3D face recognition approach. Our approach automatically detects nose tip and is making use of 15 sub regions on the face. The modified face recognition algorithm is evaluated on Bosphorus dataset. We achieve a Rank one recognition rate of 99.3%. Artifacts and incomplete facial data are still major problems in face recognition experiments. Rank based score and hierarchical contour based registration yields better results.

REFERENCES

[1] P. Jonathon Phillips, Patrick J. Flynn, Todd Scruggs, Kevin W. Bowyer, Jin Chang, Kevin Hoffman, Joe Marques, Jaesik Min, and William Worek, "Overview of the face recognition grand challenge," in CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Volume 1, Washington, DC, USA, 2005, pp. 947–954, IEEE Computer Society.

[2] P. J. Phillips, J. R. Beveridge, B. A. Draper, G. Givens, A. J. O'Toole, D. Bolme, J. Dunlop, Y. M. Lui, H. Sahizada, and S. Wiemer, "An introduction to the good, the bad, and the ugly challenge problem," in IEEE International Conference on Automatic Face and Gesture Recognition, 2011, pp. 346– 353. 1, 2, 3

[3] J. R. Beveridge, P. J. Phillips, G. H. Givens, B. A. Draper, M. N. Teli, and D. S. Bolme, "When high-quality face images match poorly," in IEEE International Conference on Automatic Face and Gesture Recognition, 2011, pp. 572– 578. 2, 3

[4] Aggarwal, GauravBiswas, SomaFlynn, Patrick J.Bowyer, Kevin W. Proceedings of IEEE Workshop on Applications of Computer Vision, Predicting good, bad and ugly match Pairs, 2012, pp.153-160

[5] Lei, Y., Bennamoun, M., & El-Sallam, A. A. (2013). An efficient 3D face recognition approach based on the fusion of novel local low-level features. *Pattern Recognition*, *46*(1), 24–37.

[6] R.Reji, S .Ravi, Comparative Analysis in 3D face Recognition, 2010-Special Issue International Journal of Imaging Science and Engineering. ISSN 1934-9955

[7] Savran, N. Alyuz, H. Dibeklioglu, O.Celiktutan, B. Gokberk, B. Sanur, and L.Akarun, "Bosphorus Database for 3D Face Analysis," The First COST 210lWorkshop on Biometrics and Identity Management (BIOID 2008), Roskilde University, Denmark, 7-9 May 2008.

[8] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Computing. Survey, vol. 35, no. 4, pp. 399–458, 2003.

[9] K. Bowyer, K. Chang, and P. Flynn, "A survey of approaches and challenges in 3D and multi-modal 3D+2D face recognition," Computer Vision Image Understanding, vol. 101, no. 1, pp. 1–15, 2006.

[10] K. Chang, K. W. Bowyer, and P. Flynn, "Multiple nose region matching for 3D face recognition under varying facial expression," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 10, pp. 1–6, Oct. 2006.

[11] Faltemier, Timothy C., Kevin W. Bowyer, and Patrick J. Flynn. 2008. "A Region Ensemble for 3-D Face Recognition." *IEEE Transactions on Information Forensics and Security* 3 (1): 62–73. doi:10.1109/TIFS.2007.916287.

[12] C. Zhong, Z. Sun, T. Tan, Robust 3D face recognition using learned visual codebook, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2007, pp. 1–6.

[13] X. Lu, A. K. Jain, and D. Colbry, "Matching 2.5D face scans to 3D models," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 1, pp. 31–43, Jan. 2006.

[14] J. Cook, V. Chandran, and C. Fookes, "3D face recognition using log-gabor templates," in Proc. British Machine Vision Conf., 2006, pp. 83–92.

[15] A. Mian, M. Bennamoun, R. Owens, An efficient multimodal 2D and 3D hybrid approach to automatic face recognition, IEEE Transactions on Pattern Analy- sis and Machine Intelligence 29 (11) (2007) 1927–1943

[16] C. Queirolo, L. Silva, O. Bellon, 3D face recognition using simulated annealing and the surface interpenetration measure, IEEE Transactions on Pattern Analysis and Machine Intelligence 32 (2) (2010) 206–219.

[17] Anuar, L. H., Mashohor, S., Mokhtar, M., & Wan Adnan, W. A. (2010). Nose tip region detection in 3D facial model across large pose variation and facial expression. *International Journal of Computer Science Issues*, *7*(4), 1–9.

[18] Drira, Hassen Boulbaba, Ben Amor Anuj, Srivastava Daoudi, Mohamed Slama, Rim 3D Face Recognition Under Expressions,Occlusions and Pose Variation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2013,pp.1-15

[19] Lei, YinjieBennamoun, Mohammed El-Sallam, Amar A. An efficient 3D face recognition approach based on the fusion of novel local low-level features, Pattern Recognition, 2013,pp 24-37

[20] Thomas Maurer, David Guigonis, Igor Maslov "Performance of Geometrix ActiveIDTM3D Face Recognition Engine on the FRGC Data," in CVPR '05: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), Washington, DC, USA, 2005, IEEE Computer Society.