International Journal of Advanced Information Science and Technology (IJAIST) ISSN: 2319:2682
Vol.4, No.1, January 2015 DOI:10.15693/ijaist/2015.v4i2.101-105

3D Face Recognition and Face Annotation with Icp Features

B.Muthukarthiga-1,M.Rashini-2,C.Sivasankari-3,T.Varalakshmi-4.

1-Faculty,Department of ECE,UCETW,Madurai
2-Student, Department of ECE,UCETW,Madurai
3- Student, Department of ECE,UCETW,Madurai
4- Student, Department of ECE,UCETW,Madurai

Abstract— **Face recognition has been one of the most interesting and important research field. we propose a novel technique of authentication 3D face images using the face annotation. For initially we construct the 3D face images. In that images we detect the face parts. The detected face part is passed to ICP Feature Extraction. The algorithm iteratively used to minimize the distance from the source to the reference point. Based on the Euclidean calculation, the result will be predicted. In existing LDA is used for the feature extraction. The standard LDA can be seriously degraded. LDA doesn't change the location but only tries to provide more image separability. It is the reverse process of obtaining 2D images from 3D scenes. It is identified based on the true and false positive of the recognition.**

Index Terms---*Face recognition, Face annotation, 3D Construction*

I.Introduction

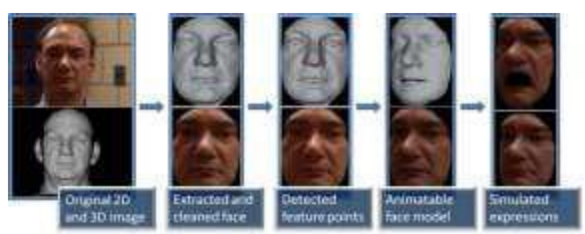
RECOGNITION of humans has become a substantial topic today as the need for security applications grow continuously. Biometry enables reliable and efficient identity management systems by exploiting physical and behavioral characteristics of the subjects which are permanent, universal and easy to access. The motivation to improve the security systems based on single or multiple biometric traits rather than passwords and tokens emanates from the fact that controlling a person's identity is less precarious than controlling what he/she possesses or knows. Additionally, biometry-based procedures obviate the need to remember a PIN number or carry a badge. Each having their own limitations, numerous biometric systems exist that utilize various human characteristics such as should be taken into account as well as the purposes of use-context that include technical, social and ethical factors [1]. For instance,while fingerprint is the most wide-spread biometric trait from a commercial point of view [2](mainly due to a long history in forensics), it mostly requires user collaboration. Similarly,iris recognition, which is very accurate, highly depends on the image quality and also requires significant cooperation from the subjects. Face recognition stands out with its favorable reconcilement between accessibility and reliability. It allows identification at relatively long distances for unaware subjects that do not have to cooperate. Like other biometric traits, the face recognition problem can also be interpreted as identification or verification of one or more persons by matching the extracted patterns from a 2D or 3D still image or a video with the templates previously stored in a database. Despite the fact that face recognition has been drawing a never-ending interest for decades and major advances were achieved, the intra-class variation problems due to various factors in real-world scenarios such as illumination, pose, expression, occlusion and age still remain a challenge. Systems that extract shape information from 2D images, e.g. passive stereo approach, rely on the knowledge of extrinsic parameters of the scene and intrinsic parameters of the camera to obtain a certain degree of accuracy. On the other hand, with active sensors like laser scanners, a scan can take several seconds.

It requires iris, voice, face, fingerprint, gait or DNA. "Superiority" among those traits is not a realistic concept when it is parted from the application scenario. The system constraints and requirements the subject to remain still during the process and furthermore reconstruction of depth is limited to short range. However, this does not hold for expressions which alter the facial surface characteristics in addition to appearance. In order to achieve realistic facial expression simulations, we propose an automatic procedure to generate MPEG-4 compliant animatable face models from the 2.5D facial scans (range images) of the enrolled subjects based on a set of automatically detected feature points. Using a facial animation engine, different expressions are simulated for each person and the synthesized images are used as additional gallery samples for the recognition task. It is important to emphasize that synthetic sample augmentation is carried out during enrollment only once for each subject.

A.Existing Work on 3D Assisted 2D Face Recognition

Possible solutions for illumination and view point invariance in 2D face recognition are limited due to the 3D nature of the problem. By incorporating the 3D shape data of the face, researchers aim to improve 2D recognition performances in the presence of such variations. On the other hand, acquisition of facial models using 3D scanners can be problematic in the operational mode, especially under the scenario of uncooperative persons to be recognized. Mainly due to these two factors, the idea of 3D shape assisted 2D face recognition emerged, for which 3D shape can be reconstructed based on the captured 2D images or it can be acquired asymmetrically during the enrollment phase. Methods based-on 2D images as their unique modality try and extract the 3D shape from the available data. In [5], a shape-from-shading (SFS) based method is proposed to generate synthetic facial images under different rotations and illuminations. In [6], a 3D generic face model is aligned onto a given frontal image using 115 feature vertices and different images are synthesized with variant pose, illumination and expression. Example synthetized faces from [5] and [6] are given in Fig. 1. A similar scheme is also presented in [7], where a personalized 3D face is reconstructed from a single frontal face image with neutral expression and normal illumination using 83 automatically located feature points (Fig. 2). Another study [8] presents a combination of an edge model and color region model for face recognition, after synthetic images with varying pose are created via a deformable 3D model. In [9], a 3D morphable model is used to generate 3D face models from three input images of the enrolled subjects.

Similar to previously mentioned studies, the generated 3D models are utilized to augment the 2D training set with synthetic images rendered under varying pose and illumination conditions. Lately, a study in which 3D model reconstruction is achieved by applying the 3D Generic Elastic Model approach is published [10]. Instead of enlarging the training set, they choose to estimate the pose of the test query and render the constructed 3D models at different poses within a limited search space about the estimated pose. Differently from these mentioned methods, an important class of approaches that relies on 3D morphable models (3DMM) uses 3D data as an intermediate step for 2D face recognition. Two compensations are reported to improve the 2D face recognition performance. Employing a combined enrollment with 2D and 3D data eliminates the risk of faulty face reconstruction. This potential scenario was also proposed during the Face Recognition Grand Challenge (FRGC), where enrolled images are 3D and the target images are still 2D images [19] but no baseline was provided. Reinforcing this trend, in their analysis [20], 17 feature points are detected automatically and utilized to produce an MPEG-4 compliant animatable model for each subject by warping a generic head using Thin Plate Spline (TPS) method.



The enrollment procedure is illustrated on an example.

The main contribution of this paper revolves around this last stage, in which the rigid facial surface with no semantics is transformed in to a highly realistic animatable model. Once this model is obtained, it is animated using a compatible animation engine for various expressions. The efficacy of the generated synthetic face images are evaluated on 3 different face recognition systems. Looking back at the existing works in this domain, we observe that 3D data is mostly utilized to compensate pose and illumination changes. In fact, the facial expressions are included only in [6] and [7]. In both studies; they are handled together with other variations without any particular analysis on expression simulations. In [6], the experiments are conducted on a small database of 10 subjects, for which the gallery set is augmented by synthesizing images under different pose, illumination and expression conditions. On the other hand in [7], a larger database is utilized but the impact of the generated images is only analyzed in terms of pose variations.

II. PROPOSED SYSTEM

In the proposed system, the enrollment is assumed to be done in both 2D and 3D for each subject under a controlled environment – frontal face images with a neutral expression and under ambient illumination. The obtained 3D shape of the facial surface together with the registered texture is preprocessed, firstly to extract the face region. On the extracted facial surface, scanner-induced holes and spikes are cleaned and a bilateral smoothing filter is employed to remove white noise while preserving the edges. After the hole and noise free face model (texture and shape) is obtained, 17 feature points are automatically detected using either shape, texture or both, according to the regional properties of the face [21]. These detected points are then utilized to warp a generic animatable face model so that it completely transforms into the target face. The generic model with manually labeled 71 MPEG-4 points is suitable to simulate facial actions and expressions via an animation engine that is in accordance with MPEG-4 Face and Body Animation (FBA) specifications. Finally, in order to simulate the facial expressions on the obtained animatable model, an animation engine, called visage|life™1 is utilized. Multiple expression infused face images are generated for each subject to enhance face recognition performance.

A. 3D Construction

3D scanner outputs are mostly noisy. The purposes of the preprocessing step can be listed as:

1. to extract the face region (same in 2D and 3D images);
2. to eliminate spikes/holes introduced by the sensor;
3. to smooth the 3D surface.

Firstly, adopting the method proposed in [22], the nose tip is detected: For each row, the position with the maximum z value is found and then for each column, the number of these positions is counted to create a histogram.

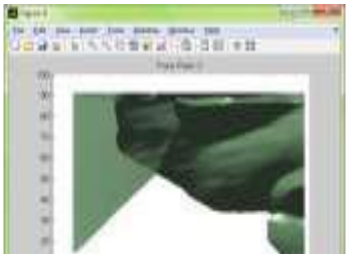
B. Face Parts Detection

Bearing in mind that subject cooperation is required during the enrollment, we base our system on the assumption of a well-controlled acquisition environment in which subjects are registered with frontal and neutral face images. In accordance with our scenario, we aim to extract a subset (17 points) of MPEG-4 Facial Definition Parameters (FDPs) to be utilized for the alignment of the faces with the animatable generic model. For the extraction of the points, 2D and/or 3D data are used according to the distinctive information they carry in that particular facial region.

Firstly, facial midline (vertical profile) analysis is done and 5 fiducial points on that midline are detected. Based on that information; face is split into sub-regions for the coarse localization of eyes, nose and lips. After that, further analysis is done inside these extracted sub-regions to detect the points of interest. For those regions with non-informative texture (like nose), 3D data is analyzed. On the other hand for the regions with noisy surface and/or distinctive color information (like eyes), 2D data is utilized. As a result, 17 facial interest points are detected in total, consisting of 4 points for each eye, 5 points for the nose and 4 points for the lips (Fig. 4) For this purpose, the row R with the minimum projection value P in the lip image is computed as:

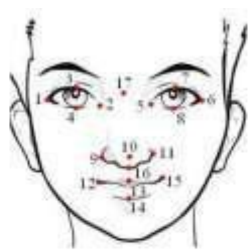
$$\boldsymbol{R} = \arg \boldsymbol{minr}\ \boldsymbol{P(r)} = \arg \boldsymbol{minr} \qquad \boldsymbol{I(p)}$$

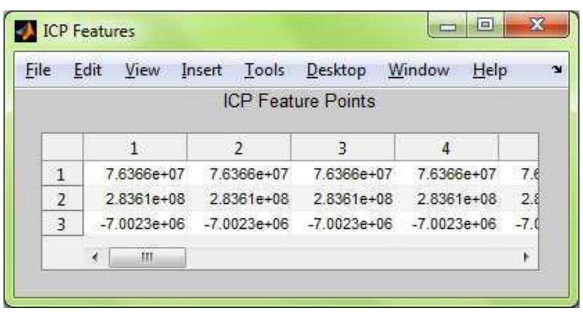
where I is the grayscale intensity. Afterwards, horizontal edges are detected in a narrow window around R, and horizontally projected in a similar fashion to detect left and right corners



C. ICP Features

ICP is stands for iterative closest points, Iterative Closest Point (ICP) is an algorithm employed to minimize the difference between two clouds of points. In the algorithm, one point cloud or the reference or target is kept fixed, while the other one the source is transformed to best match the reference. The algorithm iteratively revises the transformation needed to minimize the distance from the source to the reference point cloud.



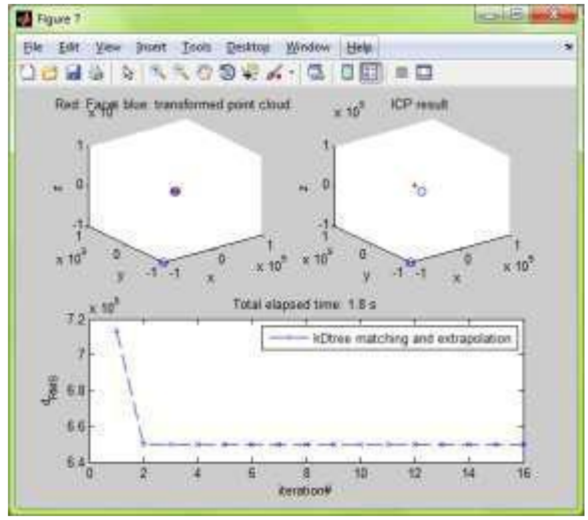


ICP Features

File Edit View Insert Tools Desktop Window Help

ICP Feature Points

	1	2	3	4	
1	7.6366e+07	7.6366e+07	7.6366e+07	7.6366e+07	7.6
2	2.8361e+08	2.8361e+08	2.8361e+08	2.8361e+08	2.8
3	-7.0023e+06	-7.0023e+06	-7.0023e+06	-7.0023e+06	-7.0



D. Recognition

In order to observe the effects of the automatic landmarking errors on the performance improvements, identification tests are conducted with both automatically detected and manually marked feature points. For 105 persons in the database, animatable models are generated and 12 expressions are simulated to create the synthetic gallery images. All images in both gallery and probe sets undergo the same preprocessing steps as in the FRGC experiments. Using a single neutral image per person, the rank-1 identification rate for PCA is found to be 63.83%. With the addition of synthetic gallery images, generated by using the manually marked feature points, the rate rises to 70.79%. Whereas, the increase using synthesized gallery images that are created based on automatically detected landmarks is a bit lower (69.71%). A similar trend is also observed for the LDA method. On the other hand, the rank-1 identification rate with LBP method is observed to be slightly higher with the points that are detected automatically when compared to the ones that are manually marked. The CMC curves for all methods and galleries are given in Fig. 15. Additionally, recognition rates are presented in Table IV in more detail. These results are very impressive in the sense that despite the errors in the automatic detection of landmarks, using these points for simulated image generation leads to a comparable amelioration in results with the ones created using manually marked points. The reason behind this result lies in the fine warping step in the animatable model generation process. At this stage, the landmarks are left aside and the correspondences are created by pairing every second point on the generic model to the closest vertex in the face scan.

III. CONCLUSION

Here we have shown the 3d face recognition process with help of Euclidean distance and ICP features It shows the better performance than the existing system

REFERENCES

[1] Nesli Erdogmus,Jean-Luc Dugelay, , "3D Assisted Face Recognition : Dealing with expression variations," IEEE Transaction on Information Forensics and Security, Vol 9, No 5, May 2014.

[2] A. F. Abate, M. Nappi, D. Riccio, and G. Sabatino, "2D and 3D face recognition: A survey," *Pattern Recognit. Lett.*, vol. 28, no. 14, pp. 1885–1906, 2007.

[3] J. P. Phillips, P. Grother, R. J. Michaels, D. M. Blackburn, E. Tabassi, and M. Bone, "FRVT 2002 evaluation report," in *Proc. IEEE Int. Workshop Anal. Model. Faces Gestures*, Oct. 2003, pp. 1–44.

[4] J. P. Phillips *et al.*, "FRVT 2006 and ICE 2006 large-scale experimental results," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 5, pp. 831–846, May 2009.

[5] W. Y. Zhao and R. Chelappa, "SFS based view synthesis for robust face recognition," in *Proc. IEEE Int. Conf. Autom. Face Gesture Recognit.*,Jan. 2000, pp. 285–292.

[6] X. Lu, R.-L. Hsu, A. K. Jain, B. Kamgar-Parsi, and B. Kamgar-Parsi, "Face recognition with 3D model-based synthesis," in *Proc. Int. Conf. Biometric Authentication*, 2004, pp. 139–146.

[7] Y. Hu, D. Jiang, S. Yan, L. Zhang, and H. Zhang, "Automatic 3D reconstruction for face recognition," in *Proc. IEEE Int. Conf. Autom. Face Gesture Recognit.*, May 2004, pp. 843–848.

[8] M. W. Lee and S. Ranganath, "Pose-invariant face recognition using a 3D deformable model," *J. Pattern Recognit.*, vol. 36, no. 8, pp. 1835–1846, 2003.

[9] J. Huang, B. Heisele, and V. Blanz, "Component-based face recognition with 3D morphable models," in *Proc. Int. Conf. Audio Video-Based Biometric Person Authentication*, 2003, pp. 27–34.

[10] U. Prabhu, J. Heo, and M. Savvides, "Unconstrained pose-invariant face recognition using 3D generic elastic models," *IEEE Trans. Pattern Anal.Mach. Intell.*, vol. 33, no. 10, pp. 1952–1961, Oct. 2011.