A Survey on Side View Based Face Recognition

Ashutosh Chandra Bhensle[1] Rohit Raja[2]
[1,2]Department of Computer Science and Engineering
[1,2]Csvtu, Bhilai FET, SSGI, Bhilai, India

Abstract— Face recognition using Side-view is a difficult problem with numerous applications. In real-life scenarios where the environment is uncontrolled, dealing with pose variations up to side-view positions are a significant task for face recognition. In this paper, we talk about the use of side view face recognition systems used in safety applications. Our objective is to recognize persons. Here, we compare available databases suitable for this task, and re-examine current methods for face recognition.

Keywords: Face recognition, Life scenarios, Databases.

I. INTRODUCTION

Face recognition is a broadly used biometric technique with many advantages of being non-intrusive, usual and unreceptive. In recent times, many applications including surveillance systems, smart homes, or any application dealing with discover people from videos use face recognition as main biometric. Mainly in uncontrolled environments, it is a challenging task to recognize faces due to occlusion, expression, or pose variations. One possible implementation area for face recognition techniques is home safety applications. By reason of the busy schedule of the parents, overlooked risks or external threats, many people suffer from accidents and injuries happening in the home environment. It is possible to stop these accidents by increasing the situational knowledge and face recognition is one of the methods that can be used for this principle. Our aim is to review recent face recognition techniques dealing with pose variants. We will follow a similar structure as in [1] and group the existing techniques into two broad categories: feature-based techniques, and image-based techniques. In feature-based techniques, pose variation is handled at the feature level, where either selected features are robust to pose variations or for registration the features are transformed accordingly. On the other hand, in image-based techniques, the images are warped or synthesized using 2D or 3D-aided systems to cope with varying poses.

II. OBJECTIVE OF THE STUDY

In There are a number of face databases containing side-view images. Most of the available databases are collected in controlled settings such as regular background, lighting changes or restricted pose variations. The CMU-MultiPIE is the largest on hand database, with 337 subjects and 15 poses. It is an extended version of the CMU - PIE database, which contains only 68 subjects and 13 poses. One more database that is mostly used in side-view face recognition applications is FERET database, containing 200 subjects and 9 pose variations.

There are also some databases that are collected in more uncontrolled situations. UHDB1 database has 16 captured of 141 subjects, where the subject is sitting in a car, and a camera placed at right angle to the subject is capturing the prospect. The recorded data contain 7 captures of different poses in an unbiased expression and one chapter with a happy expression. In addition to these, five 3D captures in different poses of the same subjects are also included in the database. MMI database is a web-based facial expression database, including 1500 samples of 19 people. It encloses both static images and image sequences of faces in frontal and in profile view displaying various expressions. 3D face databases, infrared databases, or databases containing multi-modal information may also be used for side-view face recognition. The XM2VTS database contains 4 recordings of 295 subjects acquired over a period of 4 months. All recordings contain a speaking head shot and a rotating head shot. The database has high quality color images, video sequences, sound files and a 3D Model. It is a wing of the M2VTS database, which contains voice and motion sequences of 37 people and people have been asked to count from ‘0’ to ‘9’ in their local language, and rotate the head from −90 to +90.

The Bosphorus Database is a 3D face database that includes a rich set of expressions, various poses and many types of occlusions. Although there are a number of valuable face databases containing pose variations and side-view face images, they are mostly collected in a controlled environment, where the head pose is especially restricted. Even though there are some databases, that have videos of people in less controlled situations, they either contain small pose variations, or an unrealistic scenario. As a result, a database collected in a real-world scenario, and containing large pose variations would be necessary for further face recognition applications.

III. METHODS

Side-view face recognition is an exigent problem due to the complicated 3D structures of human faces. It is an extremely important task in any real-world application, where the environment is uncontrolled, and head pose is unrestricted. Here, we review available methods that are dealing with side-view face recognition. We can categorize the methods according to the technique used for dealing the pose differences between the library images and the test images. One promising approach is to modernize the feature space. An additional method is to generate synthetic images from the library images to acquire images under pose variation. We will examine these methods in the next section. We also review some relevant approaches that make use of side-view face images, but either use additional modalities, or execute different applications than face recognition.

A. Feature based recognition:

In feature-based face recognition methods, registration and recognition of faces are based on the extracted features. In other words, when the input image and the gallery image are in different poses, either the transformation in feature space is learned and applied to extract features to handle pose variations, or features that are robust to pose variations are used. Since we are interested in identifying people using side-view face images, we categorized the methods according to their relevancy. We take into consideration, if the method uses side-view face images for enrolment, if the images are acquired from the video, if a 2D color camera is used, if the data is gathered in unrestricted condition, and if the aim is face recognition.

Harmon [10] uses profiles of 256 subjects and selects 9 fiducial points, from which they derive 11 features and calculate the similarities using Euclidean Distance. They improved their method in [11] by decreasing the number of features to 10. Later on, Harmon [12] defined 17 fiducial points, and reported a recognition rate of 96% in a database of 121 persons. Wu and Huang [13] developed a facial recognition technique using 24 fiducial points, where they take out the face image using Cubic B-splines and compute the landmarks repeatedly. They account that 17 out of 18 test images are appropriately recognized. Encouraged by these methods, the first attempts to compare side-view face images were based on comparing profile curves, fiducial points that are taken out from the profile, or features that are calculated using the fiducial points on face image.

Bhanu and Zhou [17] suggested a curvature-based matching technique for registration of side-view face images. They find the curvature of the face profile, and using the curvature values they find throat and nose. After that, they match up the curvature values between nation and throat point using Dynamic Time Warping. They evaluate their performance on Bern database and Stirling Database and reach to a recognition accuracy of 90.00% and 75.25%, respectively.

In a later work, Zhou and Bhanu [17] recommend a technique to build a high resolution face image from low resolution videos. They use an elastic registration algorithm for alignment of face images and employ recognition using Dynamic Time Warping. They accomplish experiments on 28 video sequences of 14 people walking with a right angle to the camera, and recognize more than 70% of the people correctly.

Gao and Leung [11] recommend an attributed string matching algorithm for side-view face recognition, where they match a string of line segments. They tested their performance on Bern Database and achieved an accuracy of 98.33%. In [20], they apply Hausdorff distance to measure similarity between the sets of line segments generated from edge maps of faces, and achieve 96.7% recognition accuracy on the Bern Database. Later on, in [20], Gao extended this effort by using leading points, instead of edge maps, as features for measuring similarity. He provides a Modified Hausdorff Distance for significance-based dominant point matching as well. The testing on Bern data set confirm an accuracy of 94.17%, and achieved a significant decrease in average storage space by 81.5%. Approaches that use only profile line have limited usage in real-world applications, since they rely on clear images that do not contain pose variation. Consequently, many other methods are proposed that make use of the texture information. One more approach is to use extensions to Principal Component Analysis (PCA).

You et al. [27] apply Neighborhood Discriminate Projection for face recognition, where they plan to preserve within-class neighboring geometry during are differentiating the projected vectors of samples of dissimilar classes. Their performance in UMIST database is publicized to be 96.89%.

Lucey and Chen [28] introduce a method “patch whole algorithm”, for verification of meagerly registered faces. They achieved the equal error rate of 12.00 on FERET database. Cheung et al. [29] suggest a method to recognize faces from surveillance cameras using Elastic Bunch Graph Matching (EBGM), and on FacePix database they achieved an accuracy of 97:00%.

B. Image based recognition:

In image-based face recognition techniques, when the input image and the library image are in dissimilar poses, a new image from either library image or input image is synthesized by warping or with the aid of a 3D face reconstruction system. Hence, the pose variation is handled by synthesizing images that contain the same pose as the image that is compared to.

Beymer and Poggio [30] use preceding knowledge of 2D face images under different rotations, to create virtual views of a known face. After that, one real and multiple virtual views are used for enrollment. In order to create virtual views, the shape and texture features are vectorized. Subsequently, using optical flow and template matching, the correlation between the images and an average face image is calculated. In the next, the normalized correlations are compared to recognize the face. In more one example, 14 virtual images as enrolment, 62 people are recognized in a cross-validation methodology, and a recognition accuracy of 70:20% was achieved.

Wallhoff *et al.* [31] join artificial Neural Networks (ANN) and Hidden Markov Models (HMM), where they produce the rotation process of frontal views to profile views using an ANN, and class by HMM. They check their system on the Mugs hot database and reach accuracy to 56:00% of 100 individuals. Afterward, they present an improved system in [32]. Here they fuse profile views using Multi Layer Perception (MLP) with PCA weights, and attain smoother images. Subsequently, they apply a hybrid system of HMM/RBF for classification. They accomplish an accuracy of 60:00% of 100 persons on the Mugs hot database.

IV. CONCLUSION

In paper, we have presented a review of the current side-view face recognition techniques. It is an essential task to recognize persons from side-view angles, particularly in real-world applications such as surveillance systems, smart homes, or any application dealing with identifying people in recorded videos. In such applications, the environment is uncontrolled, and therefore head pose is unrestricted, lighting is variable, and expression may be evident. Initially we compared available databases that hold side-view face images or videos, and noted that there is still a requirement for a face recognition database collected from challenging environments, and containing real-world scenarios. Next, we reviewed existing methods for side-view face recognition. We have observed that, especially recent works are more relevant to the subject, since they are based on real-world scenarios. They put more importance on side-view face recognition and pose variations, and they use recorded videos in place of stationary images. There are also various research using side-view images or image sequences, to recognize facial action units, or information like gender.

Even though they do not plan to recognize faces, their techniques might be also useful for face recognition techniques. For that reason, we also described these works in this paper. In the existence of pose variation, one of the most vital issues is registered. In most of the presented methods, people use fiducial points on the face as features for listing. When there is only one image available in the library, people either create new images with different poses, or they use features that are healthy for pose variation.

` Though, in the applications where more images, or video sequences are presented, it is possible to categorize images according to pose angle and compare only images with similar poses. When the registration is handled, features that illustrate side-view face images are needed. In many of the systems, the profile sketch is used as a means of biometric feature. Yet, additional fiducial points are used, or texture information is added using methods like Gabor filtering, Histogram of Oriented Gradients, or PCA, the performance is made known to be improved.

REFERENCES

[1] Zhang, X., Gao, Y.: Face recognition across pose: A review. Pattern Recognition 42(11), pp. 2876–2896, (November 2009).
[2] Sim, T., Baker, S., Bsat, M.: The CMU Pose, Illumination, and Expression Database. IEEE Transactions on Pattern Analysis and Machine Intelligence 25 , pp. 1615–1618 ,(2003).
[3] Gross, R., Matthews, I., Cohn, J., Kanade, T., Baker, S.: Multi-PIE. Image and Vision Computing 28(5), pp. 807–813, (May 2010).
[4] Gross, R.: Face Databases. In: Handbook of Face Recognition. Springer, New York, pp. 301–327 (2005).
[5] Gao, W., Cao, B., Shan, S., Zhou, D., Zhang, X., Zhao, “The CAS-PEAL large-scale Chinese face database and evaluation protocols”, Technical report, ICT-ISVISION Joint Research & Development Laboratory for Face Recognition, Chinese Academy of Sciences (2004).
[6] Messer, K., Matas, J., Kittler, J., Luettin, J., Maitre, G.: XM2VTSDB: The Extended M2VTS Database. In: Int. Conf. on Audio and Video-based Biometric Person Authentication. , pp. 72–77 (1999).
[7] Pantic, M., Valstar, M., Rademaker, R., Maat, L.: Web-based database for facial expression analysis. In: IEEE Int. Conf. on Multimedia and Expo, IEEE, pp. 317–321 (2005).
[8] Savran, A., Alyuz, N., Dibeklioglu, H., Celiktutan, O., Gokberk, B., Sankur, B., Akarun, L.: Bosphorus Database for 3D Face Analysis. In Schouten, B., Juul, N.C., Drygajlo, A., Tistarelli, M., eds.: Biometrics and Identity Management. Volume 5372 of Lecture Notes in Computer Science. Springer, Berlin, Heidelberg, pp. 47–56, (2008).
[9] Kaufman, G.J., Breeding, K.J.: The Automatic Recognition of Human Faces from Profile Silhouettes. IEEE Transactions on Systems, Man and Cybernetics 6(2), pp. 113–121, (February 1976).
[10] Harmon, L., Hunt, W.: Automatic recognition of human face profiles. Computer Graphics and Image Processing 6(2), pp. 135–156, (April 1977).
[11] Harmon, L.D., Kuo, S.C., Ramig, P.F., Raudkivi, U.: Identification of human face profiles by computer. Pattern Recognition 10(5-6), pp. 301–312, (1978).
[12] Harmon, L.D., Khan, M.K., Lasch, R., Ramig, P.F.: Machine identification of human faces. Pattern Recognition 13(2), pp. 97–110, (1981).
[13] Wu, C.J., Huang, J.S.: Human face profile recognition by computer. Pattern Recognition 23(3-4) , pp. 255–259 , (1990).
[14] Yulu, Q., Soonthornphisaj, N.: Profile recognition using recheck procedure. In: IEEE Asia-Pacific Conf. on Circuits and Systems APCCAS, pp. 303–306, (November 1998).
[15] Liposcak, Z., Loncaric, S.: A Scale-Space Approach to Face Recognition from Profiles. In Solina, F., Leonardis, A., eds.: Computer Analysis of Images and Patterns. Volume 1689. Springer, Berlin, Heidelberg, pp. 833–834, (June 1999).
[16] Bhanu, B., Zhou, X.: Face recognition from face profile using dynamic time warping. Int. Conf. on Pattern Recognition (ICPR) , pp. 499–502, (2004).
[17] Zhou, X., Bhanu, B.: Human Recognition Based on Face Profiles in Video. In: IEEE Computer Society Conf. on Computer Vision and Pattern Recognition (CVPR’05) - Workshops, Washington, DC, USA, IEEE Computer Society (2005).
[18] Gao, Y., Leung, M.: Human face profile recognition using attributed string. Pattern Recognition 35(2), pp. 353–360, (February 2002).
[19] Gao, Y., Leung, M.: Line segment hausdorff distance on face matching. Pattern Recognition 35(2), pp. 361–371, (February 2002)
[20] Gao, Y.: Efficiently comparing face images using a modified hausdorff distance. IEEE Trans. Pattern Anal. Mach. Intell. Proc. - Vision, Image, and Signal Processing 150(6), pp. 346–350, (2003).
[21] Biuk, Z., Loncaric, S.: Face recognition from multi-pose image sequence. In: Int. Symposium on Image and Signal Processing and Analysis, pp. 319–324, (2001).
[22] Tsalakanidou, F.: Use of depth and colour eigenfaces for face recognition. Pattern Recognition Letters 24(9-10), pp. 1427–1435 (June 2003).
[23] Gross, R., Yang, J., Waibel, A.: Face recognition in a meeting room. In: IEEE Int. Conf. on Automatic Face and Gesture Recognition, Washington, DC, USA, IEEE Computer Society , pp. 294, (2000).
[24] Raytchev, B., Murase, H.: Unsupervised face recognition by associative chaining. Pattern Recognition 36(1) , pp. 245–257 , (January 2003).
[25] Kanade, T., Yamada, A.: Multi-subregion based probabilistic approach toward pose-invariant face recognition. In: IEEE Int. Symposium on Computational Intelligence in Robotics and Automation. Volume 2, pp. 954–959, (2003).
[26] Liu, C.: Gabor-based kernel PCA with fractional power polynomial models for face recognition.IEEE Transactions on Pattern Analysis and Machine Intelligence 26(5), pp. 572–581, (2004).

[27] You, Q., Zheng, N., Du, S., Wu, Y.: Neighborhood discriminant projection for face recognition. In: Int. Conf. on Pattern Recognition (ICPR), IEEE, pp. 532–535, (2006).
[28] Lucey, S., Chen, T.: A viewpoint invariant, sparsely registered, patch based, face verifier.Int. Journal of Computer Vision 80(1), pp. 58–71, (October 2008).
[29] Cheung, K.W., Chen, J., Moon, Y.S.: Pose-tolerant non-frontal face recognition using EBGM. In: IEEE Int. Conf. on Biometrics: Theory, Applications and Systems, IEEE, pp. 1–6, (September 2008).
[30] Beymer, D., Poggio, T.: Face recognition from one example view. Computer Vision, IEEE Int. Conf. on , pp. 500–507 , (June 1995).
[31] Wallhoff, F., Muller, S., Uller, S.M., Rigoll, G.: Recognition of face profiles from the MUGSHOT database using a hybrid connectionist/HMM approach. In: IEEE Int. Conf. on Acoustics, Speech, and Signal Processing (ICASSP). Volume 3., Salt Lake City , pp. 1489–1492 , (2001).
[32] Wallhoff, F., Arsic, D., Schuller, B., Rigoll, G., Stadermann, J., Stormer, A.: Hybrid profile recognition on the MUGSHOT database. In: The Int. Conf. on, "Computer as a Tool" (EUROCON), IEEE , pp. 1405–1408 , (2005).
[33] Gross, R., Matthews, I., Baker, S.: Appearance-based face recognition and light-fields. IEEE Transactions on Pattern Analysis and Machine Intelligence 26, pp. 449–465, (2002).
[34] Sanderson, C., Bengio, S., Gao, Y.: On transforming statistical models for non-frontal face verification. Pattern Recognition 39(2) (February 2006) 288–302.
[35] Gonzalez-Jimenez, D., Alba-Castro, J.L.: Toward pose-invariant 2D face recognition through point distribution models and facial symmetry. IEEE Transactions on Information, Forensics and Security 2(3) , pp. 413–429 , (August 2007).