Side-View Face Recognition

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Abstract. Side-view face recognition is a challenging problem with many applications. Especially in real-life scenarios where the environment is uncontrolled, coping with pose variations up to side-view positions is an important task for face recognition. In this paper we discuss the use of side view face recognition techniques to be used in house safety applications. Our aim is to recognize people as they pass through a door, and estimate their location in the house. Here, we compare available databases appropriate for this task, and review current methods for profile face recognition.

1 INTRODUCTION

Face recognition is a widely used biometric technique with many advantages of being non-intrusive, natural and passive. Recently, many applications including surveillance systems, smart homes, or any application dealing with identifying people from videos use face recognition as primary biometrics. Especially in uncontrolled environment it is a challenging task to recognize faces due to occlusion, expression, or pose variations.

One possible implementation area for face recognition techniques are home safety applications. Due to 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 prevent these accidents by increasing the situational awareness, and face recognition is one of the methods that can be used for this purpose.

Our goal is identifying people while they are walking through doors to estimate their location in a house or in a building. In order to preserve the privacy of the people, we will limit the range of sight of the cameras by putting them at the door frames, and use side-view face image sequences for face recognition. For this purpose, we review recent face recognition techniques dealing with pose variants.

We will follow a similar structure as in [1], and classify the available techniques into two categories: feature-based techniques, and image-based techniques. In feature-based techniques, pose variation is handled at feature level, where either selected features are robust to pose variations or for registration the features are transformed accordingly. In image-based techniques, the images are warped or synthesized using 2D or 3D-aided systems to cope with variant poses.

In Section 2 we will compare available data-sets that include side-view face images. Then in Section 3 we will review recognition and verification methods. Finally we will conclude our discussions in Section 4.

2 Available Datasets

There are a number of face databases containing side-view images. Some of them can be seen in Table 1. Most of the available databases are collected in controlled settings such as uniform background, artificial illumination changes or restricted pose variations. CMU-MultiPIE is the largest available database, with 337 subjects and 15 poses. It is an extended version of CMU-PIE database, which contains only 68 subjects and 13 poses. Another database that is mostly used in side-view face recognition applications is FERET database, including 200 subjects and 9 pose variations.

Table 1. Databases with side-view face images

Name	**Number**	**Pose**			**Illum.**	**Occl.**	**Expr.**	**3D/Color/**	**Img / Vid**
	of Subjects	**No**	**Yaw**	**Pitch**				**Gray/IR**	
CMU-PIE [2]	68	13	± 90	✓	43	glasses	4	Color	Img
CMU-MultiPIE [3]	337	15	± 90	✓	18	glasses	6	Color	Img
FERET [4]	200	9	± 90	–	✓	–	✓	Color	Img
SC-Face [5]	130	9	± 90	–	–	–	–	Color	Img
CAS-PEAL [6]	1040	21	± 90	✓	15	6	5	Color	Img
FacePix [7]	30	19	± 90	–	–	–	–	Color	Img
UMIST/Sheffield [8]	20	$19-48$	90	–	–	–	–	Gray	Img
Stirling[9]	35	3	90	–	–	–	3	Gray	Img
MUGSHOT [10]	1573	2	90	–	✓	glasses	–	Gray	Img
Bern	30	5	± 90	✓	–	–	–	B/W	Img
XM2VTSDB [11]	295	✓	± 90	✓	–	–	–	Color	Vid
M2VTS [12]	37	✓	± 90	✓	–	glasses	✓	Color	Vid
MMI [13]	19	1	90	–	–	–	✓	Color	Vid
UHDB1 [14]	141	5	± 90	–	–	–	–	3D & Color	Img
	141	17	✓	✓	✓	✓	2		Img
Bosphorus [15]	105	13	± 90	± 20	–	4	34	3D & Color	Img

There are also some databases that are collected in more uncontrolled settings. UHDB1 database contains sixteen captures of 141 subjects, where the subject is sitting in a car, and a camera placed at right angle to the subject is capturing the scene. The recorded data contains seven captures of different poses in a neutral expression and one capture with a happy expression. In addition to these, five 3D captures in different poses of the same subjects are also included to the database. MMI database is a web-based facial expression database including 1500 samples of 19 people. It contains 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. XM2VTS database contains four recordings of 295 subjects taken over a period of four months. Each recording contains a speaking head shot and a rotating head shot. The database includes high quality color images, sound files, video sequences and a 3D Model. It is an extension of the M2VTS database, which contains voice and motion sequences of 37 people, where people have been asked to count from ‘0’ to ‘9’ in their native language, and rotate the head from -90 to $+90$. The Bosphorus Database is a recent 3D face database that includes a rich set of expressions, various poses and different types of occlusions.

Although there are a number of useful face databases containing pose variations and side-view face images, they are mostly collected in controlled environment, where the head pose is very restricted. Even though there are some databases, that contain videos of people in less controlled settings, they either contain small pose variations, or an unrealistic scenario. Therefore, a database collected in a real-world scenario, and containing large pose variations would be necessary for further face recognition applications.

3 Side-View Face Recognition/Verification Systems

Side-view face recognition is a challenging problem due to the complex 3D structures of human faces. It is a highly important task in any real-world application, where the environment is uncontrolled, and head pose is unrestricted. In our task, we aim to recognize people while they are passing through doors. We will use cameras attached to door frames, and consequently tackle with side-view face recognition with some variation at head pose.

Here, we review available methods that are dealing with side-view face recognition. We categorize the methods according to the technique used for coping the pose differences between the gallery images and the test images. One possible approach is to transform the feature space, which we investigate in Section 3.1. Another possible method is to generate synthetic images from the gallery images to obtain images under pose variation. We will examine these methods in Section 3.2. Finally, in Section 3.3, we also review some relevant approaches that make use of side-view face images, but either use additional modalities, or implement different applications than face recognition.

3.1 Feature-Based Methods

In feature-based face recognition methods, registration and recognition of faces are based on 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 extracted features to handle pose variations, or features that are robust to pose variations are used. A summary of the available methods is given in Table 2. Since we are interested in identifying people using side-view face images, we categorized the methods according to their relevancy to our problem. Here, we take into consideration, if the method uses side-view face images for enrollment, if the images are acquired from video, if a 2D color camera is used, if the data is gathered in unrestricted condition, and if the goal is face recognition. Our categorization can also be seen in Table 2.

The first research on side-view face recognition was reported in late 70s by Kaufman and Breeding [16], where they reported a face profile recognition system using profile silhouettes. Their system relies on normalized circular autocorrelations as feature vectors, where they use k-nearest neighbor for classification. They reach a performance of 90% in a database of 10 people. Harmon and Hunt [17] use manually drawn profiles of 256 subjects and select nine fiducial points, from which they derive 11 features and compute the similarities using Euclidean Distance. They improved their method in [18] by reducing the number of features to 10. Later in [19], they defined 17 fiducial points, and reported a recognition rate of 96% in a database of 121 people. In 90s, Wu and Huang [20] developed a facial profile recognition method using 24 fiducial points, where they extract the profile using Cubic B-splines and calculate the landmarks automatically. They report that 17 out of 18 test images are correctly recognized.

Inspired by these methods, the first attempts to compare side-view face images were based on comparing profile curves, fiducial points that are extracted from the profile, or features that are computed using the fiducial points on face profile.

Yulu and Soonthornphisaj [21] present a facial profile recognition method using recheck procedure. First, they extract profiles and normalize them using the profile angle. They use fiducial points for matching the profiles, where they use Euclidean Distance as similarity measure. If the difference is less then a predefined threshold, the algorithm recalculates the distance discarding the components that does not contain a significant difference. They showed an accuracy of 90% using 51 profile images.

Liposcak and Loncaric [22] use the profile curve to extract twelve fiducial points using scale-space filtering. After normalizing the feature characteristics, they measure the similarity using Euclidean distance. They experiment on Bern dataset and achieve a recognition rate of 90%.

Bhanu and Zhou [23] propose a curvature-based matching approach for registration of side-view face images. They compute the curvature of the profile, and using the curvature values they find nose and throat. Then they compare the curvature values between nasion and throat point using Dynamic Time Warping (DTW). They measure their performance on Bern database and Stirling Database and achieve a recognition accuracy of 90.00% and 75.25%, respectively. In a later work [24], Zhou and Bhanu propose a method to construct a high resolution face profile image from low resolution videos. They use an elastic registration algorithm for alignment of profiles, and apply recognition using DTW. They experiment on 28 video sequences of 14 people walking with a right angle to the camera, and recognize more than 70% of he people correctly.

Gao and Leung [25] propose an attributed string matching algorithm for side-view face recognition, where they match a chain of profile line segments. They tested their performance on Bern Database and achieved an accuracy of 98.33%. In [26], 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 in [27], Gao extended this work by using dominant points, instead of edge maps, as features for measuring similarity. He also provides a Modified Hausdorff Distance (MHD) for significance-based dominant point matching. The tests on Bern dataset show an accuracy of 94.17%, and achieved a significant decrease in average storage space of 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 approach is to use extensions to Principal Component Analysis (PCA).

Biuk and Loncaric [28] use multi-pose image sequences to recognize faces. They use eigenface approach to represent faces, where from each image sequence a trajectory in eigenspaces are formed. In recognition phase they compare these trajectories. They obtain an accuracy of 96.40% on a database having videos of 28 subjects, where the subjects are asked to rotate their faces from -90 degrees to $+90$ degrees.

Tsalakanidou *et al.* [29] present a face recognition technique based on depth and color eigenfaces. Here, for exploiting the 3D information they build a depth map using the pixel intensities. They experimented on XM2VTS database using 40 subjects, and recognized 87.5% of them correctly.

Gross *et al.* [30] investigate recognition of human faces in a meeting room, where they use low quality images with poor illumination, unrestricted head poses, various facial expressions and occlusions. To handle these problems, they propose a method called Dynamic Space Warping (DSW). Here, they first create a vector of sub-images from a given face, perform PCA to each of these sub-images, and then use the sequence of these to compare using dynamic programming. They evaluate their algorithm using recordings of six meetings with six people, and achieved an accuracy of 89.4% on the images without occlusion, where as on the images including small occlusions their performance drops to 55.9%, and in presence of large occlusions they achieve an accuracy of 48.6%.

Raytchev and Murase [31] propose an online face recognition method called Associative Chaining for recognizing face image sequences obtained in real-world environments. Their method relies on chaining similar views in face-only image sequences depending on local measures of similarity, and then clustering image sequences belonging to the same subject. They experimented on a real-world data of both frontal and side-view faces of 17 people, and reported a recognition rate of 88.60%.

Kanade and Yamada [32] apply a multi-subregion based probabilistic approach for pose-invariant face recognition. For registration of the faces they manually label several landmarks and apply appearance-based template matching. Then they divide the face into 21 subregions using three manually labeled landmarks, and compute the similarities between faces using Sum of Squared Differences (SSD). Their average performance on CMU-PIE is shown to be around 80%, however the accuracy drops below 40% when the probe pose is side-view.

Liu [33] use Kernel PCA method to recognizes faces in different views. They first classify the pose by applying Nearest Neighbor Classifier (NNC) using cosine similarity measure. Then they compute Gabor-based kernel PCA for each individual pose class, and classify faces using NNC. They achieve 95.30% recognition accuracy on CMU-PIE database across five pose classes, where they have frontal, half profile and profile views of the subjects both in the gallery and in the test set.

You *et al.* [34] apply Neighborhood Discriminant Projection (NDP) for face recognition, where they aim to preserve within-class neighboring geometry while differentiating the projected vectors of samples of different classes. Their performance in UMIST database is shown to be 96.89%. Lucey and Chen [35] presents a method, called "patch-whole" algorithm, for verification of sparsely registered faces. They obtain the equal error rate of 12.00 on FERET database. Cheung *et al.* [36] propose a method to recognize faces from surveillance cameras using Elastic Bunch Graph Matching (EBGM), and on FacePix database they obtain an accuracy of 97.00%.

3.2 Image-Based Methods

In image-based face recognition techniques, when the input image and the gallery image are in different poses, a new image from either gallery image or input image is synthesized by warping or with the aid of a 3D face reconstruction system. So, the pose variation is handled by synthesizing images that contain the same pose as the image that is compared to. A summary of the available methods can be seen in Table 3.

Beymer and Poggio [37] use prior knowledge of 2D face images under different rotations, to generate virtual views of a given face. Then, one real and multiple virtual views are used for enrollment. In order to generate virtual views, the shape and texture features are vectorized. Then, using optical flow and template matching, the correlation between the images and an average face image is computed. The normalized correlations are then compared to recognize the face. Using one example, and 14 virtual images as enrollment, 62 people are recognized in a cross-validation methodology, and a recognition accuracy of 70.20% was achieved.

Wallhoff *et al.* [38] combine artificial Neural Networks (ANN) and Hidden Markov Models (HMM), where they synthesize rotation process of frontal views to profile views using an ANN, and classify by HMM. They test their system on the Mugshot database and achieve an accuracy of 56.00% for 100 individuals. Later, they present an improved system in [39]. Here they synthesize profile views using Multi Layer Perceptron (MLP) with PCA weights, and achieve smoother images. Then they apply a hybrid system of HMM/RBF for classification. They achieve an accuracy of 60.00% for 100 individuals on the Mugshot database.

Gross *et al.* [40] develop a theory of appearance-based object recognition from light-fields, where they estimate the eigen light field as the set of features for recognition. They ensure normalization of the faces using Active Appearance Models (AAM), where they find $39 - 54$ facial points depending on the pose, and then warp the image. Then, they apply the eigen light-field estimation algorithm and classify faces using nearest neighbor algorithm. They experimented on the CMU-PIE and FERET databases, and achieved accuracies of 66.30% and 75.00%, respectively.

In [41], Sanderson *et al.* extend each frontal face model with synthesized models of non-frontal views using Maximum Likelihood Linear Regression (MLLR), and multi-variate Linear Regression (LinReg). They apply this synthesis approach to two face verification systems: a holistic system based on PCA-derived features, and a local feature system based on DCT-derived features. They evaluate their methods on FERET database, and report EER of 11.51% and 10.96% for LinReg/PCA method and MLLR/DCT method, respectively.

Gonzales-Jimenes and Alba-Castro [42] build a Point Distribution Model (PDM) to identify the parameters that control the pose parameters. Then, they apply pose correction and synthesize virtual views using Thin Plate Splines (TPS)-based warping. Their face recognition system makes use of Gabor filtering. They achieve a recognition accuracy of 87.50% on the CMU-PIE database.

Table 2. Feature-based techniques for side-view face recognition.

Author(s)	**Alignment**			**Recognition/Verification**		**Experimental Setup**			**Perf.**	**Dataset**	**Relevance**
	Feature (M/A)	**Method**	**2D/3D**	**Feature (M/A)**	**Method** (R/V)	**Training**	**Gallery**	**Probe**	**(%)**		
Cheung *et al.* 2008 [36]	local facial feat. (M)	EBGM	2D	local facial feat. (A)	EBGM (R)	70	1×30	4×30	97.00	FacePix	● ● ○ ○ ○
Lucey and Chen 2008 [35]	-	-	-	fiducial pts (A)	patch-whole (V)	100	1×100	8×100	EER: 12.00	FERET	● ○ ○ ○ ○
You *et al.* 2007 [34]	–	–	–	NDP (A)	Euclidean d.	–	3×20	17×20	96.89	UMIST	● ○ ○ ○ ○
Zhou and Bhanu 2005 [24]	side-view images	elastic registration	2D	curvature (A)	DTW	–	3×14	1×14	75.20	–	● ● ● ● ○
Zhou and Bhanu 2004 [23]	nasion and throat (A)	ad hoc	2D	curvature (A)	DTW	–	2×30	1×30	90.00	Bern	● ● ○ ○ ○
	points					–	1×31	2×31	75.25	Stirling	
Liu 2004 [33]	Cosine Similarity Meas.	Nearest Neighbor	2D	Gabor-based KPCA (A)	Nearest Neighbor	–	5×68	5×68	95.30	CMU-PIE	● ● ● ○ ○
Gao 2003 [27]	nose tip and chin	ad hoc	2D	fiducial points (A)	MHD	–	1×30	1×30	94.17	Bern	● ● ○ ○ ○
Kanade and Yamada 2003 [32]	fiducial points (M)	template matching	2D	subregions (M)	SSD	13×34	1×68	13×34	80.00	CMU-PIE	● ● ○ ○ ○
Raytchev and Murase 2003 [31]	face-only img. seq. (A)	AC	2D	face-only img. seq. (A)	AC	–	–	300	88.60	–	● ● ● ● ●
Tsalakanidou *et al.* 2003 [29]	–	–	–	depth and color	nearest neighbour	–	40×2	40×2	87.50	XM2VTSDB	● ● ● ● ○
				Eigenface (A)							
Gao and Leung 2002 [26]	nose tip and chin	ad hoc	2D	profile outline (A)	Haudsorff distance		1×30	1×30	96.70	Bern	● ● ○ ○ ○
Gao and Leung 2002 [25]	nose tip and chin	ad hoc	2D	profile line segment (A)	attributed string match	–	1×30	1×30	98.33	Bern	● ● ○ ○ ○
Biuk and Loncaric 2001 [28]	–	–	–	PCA (A)	Euclidean (R)	–	1×28	1×28	96.40	–	● ● ● ○ ○
Gross *et al.* 2000 [30]	(M)		2D	PCA (A)	DSW	–	10×6	1200	89.40	–	● ● ● ● ○
Liposcak and Loncaric 1999 [22]	fiducial pts.	fixed eye and chin	2D	fiducial pts. (A)	Euclidean distance		4×30	1×30	90.00	Bern	● ● ○ ○ ○
Yulu and Soonthornphisaj 1998 [21]	profile angle (A)	normalization	2D	fiducial pts. (A)	Euclidean Distance	–	–	51	90.00	–	● ● ○ ○ ○

Prince *et al.* [43] use Tied Factor Analysis (TFA) to generate a model from images without pose, and create new images similar to observed data. After generating non-frontal faces, they use the EM algorithm to compute the distances between possible matches using a probabilistic distance metric. Their recognition performance on FERET is shown to be 86.50%.

Sivic *et al.* [44] use TV material to automatically label faces of 11 characters. First, they apply face tracking with the aid of subtitle and speech recognition. Then they localize facial features and rectify the image. Using Histogram of Oriented Gradients (HOG) descriptors they represent the faces and learn a SVM classifier to discriminate the characters. They show an accuracy of 80.57% in a database consisting of "Buffy" TV-series episodes.

Sarfraz and Hellwich [45] propose a robust face description method to eliminate strict alignment between gallery and probe images. They use pixel based appearances, and synthesize the non-frontal views to frontal using multivariate regression. The obtained prior models are then used for recognition. They report a recognition accuracy of 92.1% on FERET database, and 87.8% on CMU-PIE database.

Another approach to synthesize images is to make use of the 3D face reconstruction systems. Wai-Lee and Ranganath [46] propose a pose-invariant face recognition system based on a deformable, generic 3D face model. Here, they estimate the pose of an input face image by model matching, and synthesize the known face images in the same pose. The classification is based on least squares between texture points. They achieve recognition rates of 92.30% in a database of 15 people with four sessions and 11 scenarios including seven poses ± 90 degrees, two various illumination conditions and two different resolution conditions.

Blanz and Vetter [47] estimate 3D shape and texture of faces from single 2D images using a statistical, morphable 3D model. Using the 3D model they represent and compare faces for recognition purposes. The results on CMU-PIE and FERET show that, the algorithm achieves 95.00 and 95.90 percent correct identifications, respectively.

In [48], Liu and Chen apply a registration method, where they approximate each head with a 3D ellipsoid model for pose normalization. Here, they compare texture maps for recognition of faces. They represent each texture map as an array of local patches, and apply probabilistic modeling to each local patch. Their accuracy is shown to be around 86.00% on CMU-PIE database across nine pose classes.

Kakadiaris *et al.* [49] presents a side-view face recognition system to recognize drivers entering a gated area. For enrollment they make use of 3D face models, and extract profiles under different poses. For recognition, they extract profiles from given images and use Vector Distance Function (VDF) to match the profiles to the gallery profiles. Their system achieves a 60.00% recognition accuracy on the database UHDB1.

Efraty *et al.* [50] employ a face recognition method using 3D face model to recognize silhouette of the face profile under various rotations. First, they use 3D scans of the subjects to train an annotated face model. Then for each subject they put one profile image to gallery, and one profile image to the test set. They use the 3D face model both to estimate the pose and to classify the person. The performance of their system is shown to be 72.2% on the database UHDB1 [14].

Table 3. Image-based techniques for side-view face recognition.

Author(s)	Alignment			Recognition/Verification		Experimental Setup			Perf. (%)	Dataset	Relevance
	Feature (M/A)	**Method**	**2D/3D**	**Feature (M/A)**	**Method** (R/V)	**Training**	**Gallery**	**Probe**			
Sarfraz and Hellwich 2010 [45]	GLOH (A)	Multivariate Regression	2D	prior models (A)	LKDE (R)	9×32 9×100	1×68 1×200	13×36 9×100	87.70 92.10	CMU-PIE FERET	●●○○○
Sivic *et al.* 2009 [44]	fiducial pts. (A)	mixture of gaussians	2D	HOG (A)	MKL - SVM (R)				80.57	–	●●●●○
Prince *et al.* 2008 [43]	LIV (A)	TFA	2D	model parameters	EM (R)	220	1×100	4×100	86.50	Feret	●○○○○
Gonzales-Jimenes and Alba-Castro 2007 [42]	PDM	TPS-warping	2D	Gabor filters (A)	normalized dot product	–	1×68	12×68	87.50	CMU-PIE	●●○○○
Sanderson *et al.* 2006 [41]	–	LinReg	2D	PCA (A)	GMM	90	1×90	8×110	EER: 11.51	FERET	●○○○○
	–	MLLR	2D	DCT (A)					EER: 10.96		
Wallhoff *et al.* 2005 [39]	PCA weights (A)	MLP	2D	synth images (A)	MLP and RBF	600	1×100	1×100	60.00	MUGSHOT	●○○○○
Wallhoff *et al.* 2001 [38]	labeled rows (M)	ANN	2D	synth images (A)	HMM	2×600	1×100	1×100	56.00	MUGSHOT	●○○○○
Beymer and Poggio 1995 [37]	shape and texture features per pixel	optical flow and template matching	2D	normalized correlation		55×9	1×62	10×62	70.20	–	●○○○○
Efraty *et al.* 2009 [50]	fiducial pts. (A)	AFM	3D	ASM (A) profile	HD (R)	5×45	1×45	1×45	72.70	UHDB1	●●●○○
Kakadiaris *et al.* 2008 [49]	–	AFM	3D	profile (semi-A)	VDF (R)	5×44	3×44	2×44	60.00	UHDB1	●●●○○
Liu and Chen 2005 [48]		Ellipsoid model	3D	texture map (A)	probabilistic modeling	9×34	1×34	8×34	86.00	CMU-PIE	●●○○○
Gross *et al.* 2004 [40]	fiducial pts (A)	AAM	2D	eigen light fields (A)	nearest neighbour	13×34	1×34	12×34	66.30	CMU-PIE	●●○○○
						9×100	1×100	8×100	75.00	FERET	
Blanz and Vetter 2003 [47]	fiducial points (M)	morphable model	3D	PCA (A)	Max-LL-LDA	200	1×68	65×68	95.00	CMU-PIE	●●○○○
							1×194	9×194	95.90	FERET	
Wai-Lee and Ranganath 2003 [46]	facial features (M)	morphable model	3D	texture points (A)	least squares	–	10×15	44×15	92.30	–	●●○○○

3.3 Other Applications That Make Use Of Side-View Face Images

There are some approaches that make use of side-view face images either for recognition tasks combined with other biometrics, or for applications such as facial action unit recognition [51–53], gender classification [54, 55], or ethnicity identification [55]. We will also investigate some of these methods because of their relevance to side-view face recognition approaches. In Table 4, a summary of the available methods can be found.

Buddharaju *et al.* [56, 57] present a face recognition method using the bioheat information contained in thermal imagery. Here, the Thermal Minutia Points (TMP) are used as features. First, they estimate the pose using PCA and SVM, and match the local and global TMP structures of the input image with the gallery images. For evaluation, they built a dataset of thermal facial images with 138 subjects and 5 poses, and they achieved an accuracy of 86.00%.

Sanderson and Paliwal [58] describe a multi-modal person verification system based on speech and facial profiles. Here, they extract the profile, align using the nose location, and calculate a distance map as a similarity measure. Then they combine the results from speaker verification system with profile verification system using a Fusion and Classification Module (FCM). They present their results on M2VTS database, where they achieve an EER of 8.11% using only the profiles, and EER of 5.41% using multimodality.

Pantic *et al.* [51] try to recognize facial action units from multiple facial views, where they analyze profile-contour fiducial points in side-view videos. They apply a rule-based classifier to distinguish between different actions. In [51], they extract the extremities of the profile contour to find the fiducial points, apply a fast-direct-chaining rule-base classification method, and achieve 84.90% recognition rate. In [52], Pantic and Patras use Particle Filtering (PF) to track the facial fiducial points, and use temporal rules to recognize action units, where they achieve an accuracy of 88.20%. In [59], Pantic and Rothkrantz improved the feature extraction technique by introducing a multidetector approach. Here, they use the fiducial points both from the face profile contour and from contours of the facial components such as the eyes and the mouth. They apply a rule-based approach to recognize 32 facial action units in 454 image sequences, and achieve a performance of 86.30%. In [53], they use particle filters to track facial fiducial points, where they analyze not only changes in the contour of the face profile region, but also changes within the face region. Here, they achieve an average recognition rate of 86.60%.

Toews and Arbel [54] present a gender classification method robust to occlusion and pose variations. They propose an Object Class Invariant model (OCI) to align faces. Using the model features, the faces are classified according to gender. The equal error rate of the system is shown to be 16.30% on FERET database.

Tariq *et al.* [55] demonstrate a gender and ethnicity identification approach using face profiles. First, using Shape Context Based Matching (SCBM) they calculate the shape context, and then using Thin Plate Spline (TPS) they compute the shape context distance. They perform tests on a database containing 3D face models of 441 people, where they used silhouetted face profiles generated from these models. They obtain an accuracy of 71.20% on gender recognition, and 71.66% on ethnicity recognition.

Table 4. Other applications that use side-view face images.

Author(s)	**Alignment**			**Recognition/Verification**		**Experimental Setup**			**Perf.**	**Dataset**	**Relevance**
	Feature (M/A)	**Method**	**2D/3D**	**Feature (M/A)**	**Method** (R/V)	**Training**	**Gallery**	**Probe**	**(%)**		
Buddharaju *et al.* 2007 [57]	PCA	SVM (pose estimation)	2D	TMP (A)	hybrid TMP matching	–	5×138	50×138	86.00	–	● ○ ○ ○ ○
Buddharaju *et al.* 2006 [56]	PCA	SVM (pose estimation)	2D	TMP (A)	hybrid TMP matching	–	5×138	50×138	86.00	–	● ○ ○ ○ ○
Pantic and Patras2006 [53]	fiducial pts	PF	2D	fiducial pts (A)	rule-based method	–	–	119	86.60	MMI	● ● ● ● ○
Pantic and Rothkrantz 2004 [59]	fiducial points (A)	multidetector	2D	fiducial points (A)	rule-based method		–	454	86.30	MMI	● ● ● ○ ○
Pantic and Patras 2004 [52]	fiducial points (A)	particle filtering	2D	fiducial points (A)	rule-based method			68	88.20	MMI	● ● ● ● ○
Pantic *et al.* 2002 [51]	fiducial points (A)	transformation	2D	fiducial points (A)	rule-based method			136	84.90	MMI	● ● ● ● ○
Sanderson and Paliwal 1999 [58]	nose location	fixed nose	2D	profile and speech	FCM		3×37	1×37	EER: 5.41	M2VTS	● ● ● ● ●

4 Conclusion

In this paper, we have presented a review of the current side-view face recognition approaches. It is an important task to recognize people from side-view angles, especially in real-world applications such as surveillance systems, smart homes, or any application dealing with identifying people in videos. In such applications, the environment is uncontrolled, and hence head pose is unrestricted, illumination is varying, and expression may be apparent.

We first compared available databases that contain side-view face images or videos, and noted that there is still a need for a face recognition database collected in challenging environments, and containing real-world scenarios. Then, we reviewed available methods for side-view face recognition. Our goal is to apply side-view face recognition to house safety applications, where we aim to identify people as they pass through doors. We have seen that, especially recent works are more relevant to our subject, since they are based on real-world scenarios. They place more importance on side-view face recognition and pose variations, and they use videos instead of static images. There are also some research using side-view images or image sequences, to recognize facial action units, or information like gender or race. Even though they do not aim to recognize faces, their methods might be also useful for face recognition approaches. Therefore we also investigated these works in this paper.

In existence of pose variation, one of the most important issue is registration. In most of the available methods, people use fiducial points on the face as features for registration. When there is only one image available in the gallery, people either synthesize new images with different poses, or they use features that are robust for pose variation. However, in the applications where more images, or video sequences are available, it is possible to classify images according to pose angle and compare only images with similar poses. When the registration is handled, features that describe side-view face images are needed. In most of the systems, the profile outline is used as a means of biometric feature. However, when additional fiducial points are used, or texture information is added using methods like Gabor filtering, Histogram of Oriented Gradients, or PCA, the performance is shown to be improved.

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