A Survey: Face Recognition Techniques under Partial Occlusion

Aisha Azeem, Muhammad Sharif, Mudassar Raza, and Marryam Murtaza
Department of Computer Science, COMSATS Institute of Information Technology, Pakistan

Abstract: *Systems that rely on Face Recognition (FR) biometric have gained great importance ever since terrorist threats imposed weakness among the implemented security systems. Other biometrics i.e., fingerprints or iris recognition is not trustworthy in such situations whereas FR is considered as a fine compromise. This survey illustrates different FR practices that laid foundations on the issue of partial occlusion dilemma where faces are disguised to cheat the security system. Occlusion refers to facade of the face image which can be due to sunglasses, hair or wrapping of facial image by scarf or other accessories. Efforts on FR in controlled settings have been in the picture for past several years; however identification under uncontrolled conditions like illumination, expression and partial occlusion is quite a matter of concern. Based on literature a classification is made in this paper to solve the recognition of face in the presence of partial occlusion. These methods are named as part based methods that make use of Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), Non-negative Matrix Factorization (NMF), Local Non-negative Matrix Factorization (LNMF), Independent Component Analysis (ICA) and other variations. Feature based and fractal based methods consider features around eyes, nose or mouth region to be used in the recognition phase of algorithms. Furthermore the paper details the experiments and databases used by an assortment of authors to handle the problem of occlusion and the results obtained after performing diverse set of analysis. Lastly, a comparison of various techniques is shown in tabular format to give a precise overview of what different authors have already projected in this particular field.*

Keywords: *FR, part based methods, feature based methods, fractal-based methods, partial occlusion, recognition rates.*

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1. Introduction

Occlusion in an image refers to hindrance in the view of an object. It can be natural as well as synthetic. Natural occlusion refers to obstruction of views between the two image objects without any intension while synthetic occlusion refers to artificial blockade of intentionally covering the image's view with a white/black solid rectangular block. Partial occlusion has been found in many areas of image processing. It is seen in iris recognition where the eyelashes occlude the iris; identification via ear can also be occluded by the presence of earrings [5]. Even in real time application face image becomes occluded via accessories (sunglasses/scarf/ hair or even by hand) [50]. Other than biometric image processing, it is also encountered in medical field where the arteries may be occluded due to high cholesterol level. Presence of partial occlusion in different areas can be summarized in Figure 1.

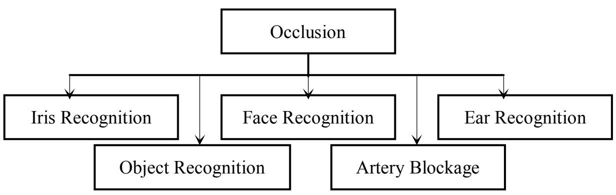

Figure 1. Presence of occlusion in different areas of image processing.

With the advancements of computer technology people misuse these developments for negative purposes. They disguise themselves in order to deceive the security system, hence affecting the performance. Considering face recognition system [61], people change their looks to trick the security system by covering the face with scarf or hand.

Literature studies reveal that faces can be recognized in a restricted environment with high accuracy [7, 67]. But in real environments it is still challenging such as illumination [70], pose variation [68] and occlusions [69] need to be overcome in which occlusions such as sunglasses, scarf [50] etc., is more important. Therefore different strategies have to be adopted to solve the problems [3, 51]. Many authors have tackled the issue of partial occlusion such as [17, 36, 53] which are described in the later sections.

Work on face recognition under controlled environments has been in scene for the past many years but recognition under uncontrolled conditions like illumination, expression [2] and partial occlusion is a recent issue. A great amount of work has been done to handle recognition under varying expressions and lighting conditions. For this, methods like Principal Component Analysis (PCA) [66], Linear Discriminate Analysis (LDA) [65], neural networks [27] and several variations of them are used but each has its limitations. Although, successful in many applications, they do not show fine performance when the face image is partially occluded. Since they are linear in nature they do not work well in non-linear cases. Several non-linear methods namely Kernel-machine-based Discriminate Analysis (KDA) [8], neural networks [27], Flexible Discriminate Analysis (FDA) [18], and Generalized Discriminate Analysis (GDA) [4], are used. But a major drawback of these methods is that they have a high computational cost in terms of training and testing the data.

Global and local features play an important role in occluded face recognition. The conventional methods used global features from one kernel [16, 41]. These features can be affected by noise or occlusions which reduces the robustness of these methods. The recognition techniques have also been used effectively using local features [6, 14, 19, 41, 52]. The partial occlusion affects the local features but the recognition methods can be made robust if these local features are merged together intelligently. Martinez [35], used robust recognition with partial occlusion by merging local features based on similarities. Support Vector Machines (SVM) [10, 58] can provide robustness if local features are treated with it.

Face recognition methods whether linear or non-linear are classified into three groups handling occlusion in face images i.e., feature based methods that deal with features like eyes, mouth, nose [46] and establish a geometrical correspondence between them. The second category is appearance-based methods that focus on the holistic features of face images by considering the whole face region and a third class deals with the hybrid local and global features of face images to be used for recognition purpose. Based on these classes a survey is conducted to analyze each individual technique in handling the partial occlusion dilemma and the enhancements made by various authors to tackle the issue. Also, listed in the text are the databases on which experiments were conducted and results were extracted after performing the tests.

2. Techniques used to Solve Partial Occlusion in Face Recognition Systems

Presented below are a number of different methods used to perform recognition under partial occlusions and varying expression. These occlusions can be real caused by sunglasses, scarf, hair etc as well as synthetic due to rectangular block. Basic methods used up till now for handling occlusion belongs to one of the following classes namely feature based methods, part based methods and fractal based methods. Figure 2 shows the work of some of the authors and description of categorized methods is illustrated in the text.

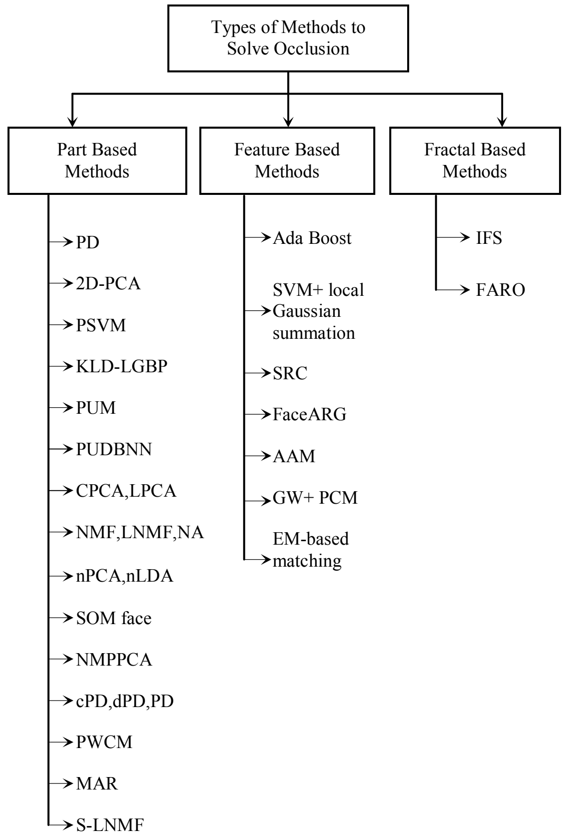

Figure 2. Types of methods used to solve occlusion in face image.

2.1. Part Based Methods

In this type of methods the face image is divided into various overlapping and/or non-overlapping parts which are then used for recognition [45]. A brief overview of techniques under this category is exemplified below.

Tan *et al.* [54] present the concepts of non-metric partial similarity between the two images while eliminating those details that are different. This partial similarity helps in extracting the intra-personal details. For this a similarity threshold is defined to determine the resemblance. Firstly, the trained and the test image is divided into sub-blocks and then projected to Self-Organizing Map (SOM) where based on the partial distance nearest neighbour is determined and the image with the least distance is used for the final identity.

So, basically the aim of the paper was to define a distance metric with the properties of automatically finding most similar parts within the two face images under comparison. Another important thing about the distance measure is that it doesn't satisfy the metric property of being self-similar and triangle inequality. So, due to this fact it is named non-metric distance measure. This distance measure is later compared with other distance measures namely Simplified Mahalanobis (SM), modified Squared Euclidean distance (SE), Weighted Angle-based distance (WA) and angle based distance between whitened feature vectors [39]. Experiments were conducted on the AR [33] face database and ORL database. From AR database a subset of 2600 images of 50 men and 50 women was taken. Before recognition the images were cropped with size equal to 66×48 pixels and histogram equalized to grey scale while in ORL database image size of 112×92 was used. Recognition Rates (RR) on both databases were 97.0% and 74.6% respectively.

In another paper, Kim *et al.* [25], present 2D-PCA for handling occlusion. Each row of the image corresponds to individual feature and finds the distorted regions of face. The reason behind is that in 2D-PCA every row of the image corresponds to a row in the feature matrix in 2D-PCA subspaces. So this method first identifies the occlusions using K-NN and 1-NN classifier and then by removing the occluded parts of face image checks partial similarity. Since occlusion detection is a one-class classification issue, for this two methods namely supervised and un-supervised methods are used to resolve the problem. In this referred paper a supervised method in combination with K-NN and 1-NN classifier is proposed. During this process when the row containing local distortion is detected, it is eliminated for the matching procedure to be applied later. Experiments were performed on AR face database with neutral frontal images. Detection method based on occlusion detection by row results in 98.00% in sunglasses and 99.00% for scarf. Similarly, when the image was divided into six sub blocks the occlusion due to sunglasses and scarf's gave 96.00%, 98.00% results respectively and finally when the image was divided in such a way that occlusion is detected after the row is transformed gave 98.00%, 98.00% recognition rates, respectively.

Jia and Martinez [22] use SVM to classify the occluded region of face. But SVM simply cannot categorize those features that have missing information as in the case of occluded parts on face image. For this the standard SVM formulation is modified to handle the missing features and is named as partial SVM. The method allows occlusion to occur in testing as well as training sets. Experiments were performed on AR face database and [40], Face Recognition Grand Challenge (FRGC) datasets. Images are cropped to a size of 29×21 pixels for AR datasets and 30×26 for FRGC.

A probabilistic method used to recognize partially occluded and varying expression faces is presented in [35]. For this face image is partitioned in to k regions and each part is analyzed via probability obtained using Mahalanobis distance. Experiments were performed on AR face database and obtained 75-85% recognition results.

Similarly in [64] Local Gabor Binary Pattern (LGBP) is used with Kullback-Leibler Divergence (KLD) for recognizing occluded faces. KLD measures the probability of occluded and non-occluded parts of face. For this LGBP operator is applied on the face images to convert them into multi-scale images and then histogram is formed for each local component which is later merged to form a single global feature vector. In the same way, Wang *et al.* [59], handled the partial occlusion using global and part detectors with the Help of Oriented Gradients (HOG) and Local Binary Pattern (LBP). On the other hand Meng *et al.* [37], use the Gabor feature [23, 47] and developed Gabor feature based Robust Representation and Classification (GRRC) system to handle the occluded faces.

In order to find the similarity among the images, histograms are intersected. This intersection of histogram eliminates those details that are different in images and take only those parts that are similar. Experiments were conducted on AR face dataset in two sessions and results were compared with other methods.

In [24], Local Salient (LS-ICA) technique using ICA architecture was used to compute the local basis of face images. Further, this method was compared with Local Non-Negative Matrix Factorization (LNMF) and Local Feature Analysis (LFA). The LS-ICA architecture retains those regions of face images that contain important facial features like eyes, lips, nose eyebrows etc., First the basis is formed and then they are aligned in order for recognition.

Method presented in [30], makes use of the extensions of Posterior Union Model (PUM) and similarity measure is determined amongst the class containing single sample [48] per class. This paper has also tried to overcome the problems of single training images and use of large feature vectors. Also, this method does not assume before where the partial occlusion would exist. Experiments performed on XM2VTS dataset and AR face database obtained recognition rates of 98.8% and 91.5%, respectively.

In [29], a Probabilistic Decision-Based Neural Network (PDBNN) approach using PUM for recognizing occluded faces is considered without prior information. Main focus of this method is on the matched features of face so as to improve the robustness of the system. XM2VTS and ORL face datasets were used in experiments and the recognition rates were 84.4% and 83.5% respectively.

In [31], feature vector based on the similarities computed against the reference images and the probe images is formed. Then LDA was used as a classifier to distinguish the separate classes. 97.41% RR was claimed on FERET database with images cropped with size of 48×54 pixels and histogram equalized.

Another such method handling occlusion is Auto-Associative Neural Network based face reconstruction method proposed in [26]. Basically the classifier is used to evoke original face from the distorted one. Once the face is recalled, the occluded parts of face are filled with the recalled ones. This process is continuously repeated in order to make the system robust to occlusions. In order to provide memory, multi-layer perceptron is used. The three layers i.e., the input, hidden and output layer perform their required functionality. Experiments were carried out on AR database in which 93 images were used for training with the size equal to 18×25 pixels. The network was trained for three types of sets; firstly pixels wise, secondly with rectangle occlusion and lastly real occlusion with sunglasses.

Three variations of PCA were used in recognizing partially occluded face images in [42]. These methods were namely Component based PCA (CPCA) in which different components of face such as eyes, mouth and nose were separately handled. Second being the holistic method in which whole face was converted into its subspace and lastly the Lophoscopic PCA i.e., LPCA was used in which those regions were identified where the occlusion was more likely to occur. After performing these tasks a fusion mechanism was used to determine the decision of separate class each image belongs to. Experiments were performed on two datasets namely AR and VISNET II which contained real occlusions. Only frontal face with neutral expression was considered in experiments. Recognition rates of the variations of PCA i.e., CPCA, LPCA with occlusion information are 72%, 47% respectively on AR dataset and 80%, 69% on VISNET II database, respectively.

Another such method that compares four different part based methods namely ICA, LNMF, NMF and Neural Associators (NA) is illustrated in [9]. In [12], PCA and LDA based methods are used to handle the expression and occluded faces. For this grey level intensities are normalized via histogram equalization and mean-variance to cancel the effect of illumination and partial occlusion. The normalized PCA and LDA are represented as nPCA and nLDA. JAFFE database was used for experimenting on the face images.

There are situations when only one reference image is available and the probe image is locally distorted or occluded [56]. In such cases recognition of face by a machine becomes difficult. For this case Self Organizing Maps (SOM) are used to perform recognition. SOM is trained in such a way that a single SOM sub space is used for all the classes and a separate SOM is trained for each individual class. Then a k-nearest neighbour strategy is used to find the unlabeled samples.

For experimental purpose AR dataset was used, the images used were of size 120×165. A basic assumption of the system was that occluded information is known in advance. The paper in [57], demonstrates a Lophoscopic PCA based method for partially occluded images and variant expressions. The use of LPCA greatly increases the performance but one major drawback of this method is its increased computational cost. UPC Face Database was used in the experiments. In [55], partial similarity based approach was used for face recognition under occlusion. Main idea for this paper was taken from the way humans perceive similarity among images, so for this a similarity threshold criterion was used. It was based on the fact that if occlusion is present it's contiguous in nature. Experiments were performed on FERET, AR and ORL database.

Method presented in [21], shows reconstructed method for partial occluded faces. Various weighting factors were assigned to distinct regions of face. AR dataset was used in experiments; the algorithm can perform efficiently when 20% of image is occluded.

Another more recent work presented in [62] deals with subspace learning and is discussed with occlusion and image misalignment. Occlusion can be detected using the L1 norm minimization by taking the difference between misaligned image and reconstructed image. So, far no work has been done to study the work related to spatial misalignment and occlusion. For experimental purpose Yale, ORL CMU PIE and FRGC datasets were used.

In [38], a Selective Local Non-Negative Matrix Factorization (S-LNMF) based method for occlusion based face recognition was proposed. For this the face images were divided into non-overlapping parts. For each part PCA was applied and then 1 NN classifier was used to detect distortions in the sub space. For comparison LNMF was used on non-occluded parts and Euclidean Distance finds the best match. For experiments AR face database was used with normal frontal faces. Aligning the eye positions normalizes the images and by eliminating the background the images were cropped to size of 64×88 pixels. This experiment was performed using 12 different ways of partitioning the image in which different sub space methods are compared.

A localized non-linear feature selection method is defined in [15] which claim to be robust in varying illumination and partial occlusions. Kernel Eigenspace is used for feature extraction; the sub parts of the neighbourhood are later merged in phase congruency images of reference images. AR dataset was used in experiments to test the functionality of the method. Its results are claimed to be 99.5% accurate. A concise text about fractals based methods is outlined in later section.

2.2. Fractal Based Methods

Marsico *et al.* [32] present Partitioned Iterated Function System (PIFS) based face recognition. PIFS based algorithms compute self-similarities among the image and establish a relationship between the squares of grid region. But PIFS algorithm is sensitive to occlusions, so to avoid this individual component of face i.e., eyes, mouth and nose are handled locally. Further distortions are removed by ad-hoc distance measure.

Experiments were performed using AR face database [33]. Before applying recognition process the images were pre-processed to same size having fixed the centre of both eyes and centre of mouth at same location every time. Another fractal based method for handling partial occlusions is outlined in [1]. Firstly the images are divided into number of sub regions and each is accessed by the iterated function system. The ad hoc distance measure eliminates extra information which is not required during the recognition phase. Subsequent section deals with feature based approaches for handling partially occluded face images.

2.3. Feature Based Methods

Feature based methods that deal with the problem of occlusion take into consideration the individual features [43], like areas around eye, nose and mouth region and ignore the other features that can be distinctive among various individuals. Probability is considered to whether the image found its correct match [34]. Method presented deals with partial occlusion and imprecise localization. For this image is divided into distinct local parts which are analyzed in isolation in the Eigenspace. This also helps in learning of the subspace under uncontrolled conditions like illumination or partial occlusions. Image localization is the initial step on detecting the occlusion in any image. This helps in aligning the centre location of eye, mouth and nose etc. Secondly the localized parts are analyzed individually in the Eigenspace in order for the system to learn, hence creating the training set. For experimental purpose 100 images of 50 men and 50 women were selected from AR face dataset. For pre-processing stage the images were resized to 120×170 pixels, all grey scaled. Recognition rate under occlusion due to scarf and sunglasses were reported to be approximately 85-95% and ~80%, respectively.

Another such method which makes use of probability is illustrated in [13]. In this method soft masking was used to classify the outlier such as occlusion in face images. Experiments on MIT face database demonstrates that an effective probabilistic match is found in images even if they are deviated by contrast of occlusion. 95% recognition results were obtained by the proposed algorithm namely EM matching when images were occluded.

Techniques under graph-based also illustrate the fact that image reconstruction or image completion via graphical model is a hot issue. Taking this fact into consideration new algorithm namely guided label learning [11] was proposed which assists in occluded face to be reconstructed. This method makes use of sparse representation and graphical model for face recognition under partial occlusion. For this, the first step is to group together the test image which results in similar sparse signal. Then based on this image best match is used for reconstruction of missing parts of image. Experiments were performed on AR face database; firstly the segmentation method named graph cut was used to find the partially occluded region of face. Then the algorithm proposed was used for the reconstruction purpose. 847 un-occluded images were used in the training phase and tests were applied on the partially occluded faces which were grouped into two classes, one with occlusion due to scarf and other due to sunglasses. PCA and Gabor PCA were used to evaluate the recognition rate with and without the algorithm proposed. Active Appearance Models (AAM) constructs a mesh-like structure over the face image to mark the visible features of face. But in real time scenarios face image can be partially occluded due to hair, hand or sunglasses etc. So, in this case fitting the mesh over the facial feature is a great job. One such approach is presented in [63], which demonstrated the AAM with adaptive fitting strategy to detect partially occluded images. IMM face database is used in the experiments by considering synthetic occlusions. Algorithm for fitting worked effectively in the presence of 10-40% occlusion in face image whereas simple fitting methods failed in the existence of occlusion.

One such method is outlined in [28] in which the algorithm used identifies those unique features that help in identifying occluded face images. Ada Boost algorithm was used in which the features were compared one against all and one against one basis. Experiments on AR dataset were performed in which the image size was 40×40 pixels. Another method under this category deals with the SVM in combination with Gaussian summation kernel [20] to deal with local distortion like occlusion on face images. Since holistic methods were greatly affected by such distortion, local features were specifically used for this purpose. For this local kernel was appropriate in identifying the features in occluded images. The main advantage of using the summation kernel method was that it’s robust to occlusions and it also satisfies Mercer’s theorem while simple kernels do not satisfy the theorem. Experiments were performed on AR dataset which contained real occlusions and test with artificial occlusion was also conducted. In [60], the technique presented is based on sparse representation to be used as classification procedure. The reason being is its discriminative power and its property of representing the input signal with most compact representation while eliminating less useful information.

The paper also assumes that if enough probe images of each individual were available in the testing phase, they can be arranged in a linear manner. Recognition was based on images with frontal views; main emphasis was laid on the fact that for feature to be properly extracted sparse nature of signals should be correctly exploited. Since occlusion or errors are sparse in nature so they don’t usually affect the pixels greatly. Performance on various databases shows that algorithm executes effectively.

3. Discussion

After reviewing different methods proposed by various authors, it can be concluded that most of the work is done under the class of part based methods. These methods usually convert the image into subspaces by dividing the image in non-overlapping blocks [49] and then applying appropriate subspace reduction technique. Such methods to be precise are PCA, LDA, ICA, NMF and LNMF etc. While those belonging to feature based methods include Ada-Boost and SVM based schemes which further use Gasussian mixtures or Eigenspaces to evaluate their procedure. Less work is done using fractal based approach to particularly handle the partial occlusion. Like stated earlier in the text none of the methods are designed to handle all the challenges a face image goes through like distortions, expressions, illuminations etc. In the above content mainly partial occlusion in face recognition has been focused and various methods used by different researchers have been discussed. A brief analysis of the aforesaid techniques is structured in a tabular format in Table 1.

Table 1. Comparison of different techniques handling partial occlusion in face recognition systems.

S. No.	Methods	Training Sets	Testing Sets	Recognition Results (%)			Types of Data-Base Used	Size of Image Used in Experiments	Comparison with Other Methods (if any)	Publication Year
1	[54]	700 in AR dataset 5 images/ person in ORL dataset	1900 in AR dataset 5 images/person in ORL dataset	97.0% in AR and 74.6% in ORL dataset			AR face dataset and ORL	66×48 in AR 112 × 92 in ORL	Bayesian method, KPCA, KFLDA, and subspace algorithms Eigenface, Fisherface and Lapalacian face	2006
2	[25]	35 sunglass images and 35 scarf images of 20 men and 15 women	100 sunglass images and 100 scarf images for testing	types of division of images	sun-glasses	scarf	AR face database	N/A	1-NN, Eigenface NMF method local NMF (LNMF)	2007
3				occlusion detection by row	98.00%	99.00%				
4				occlusion by 6 block regions	96.00%	98.00%				
5				occlusion detection by row after image transformation	98.00%	98.00%				
6	[22]	1200 images from AR and 800 images from FRGC	N/A	# of training sets	# of testing sets	results	AR face database and FRGC	29×21 pixels for AR datasets and 30×26 for FRGC.	N/A	2009
7				[a,e,f]	[b,c,d]	88.9%				
8				[a’,e’,f’]	[b’,c’,d’]	90.8%				
9				[a,b,c,e,f]	[d]	88.2%				
10				[a,b,c,e,f]	[d’]	58.8%				
11				[a,b,c,e,f,a’,b’,c’c,e’,f’]	[d,d’]	83.5%				
12	[35]	50 randomly chosen images of persons in AR dataset	remaining used for testing	75-85%			AR face database	120×170	classical correlation algorithm	2002
13	[64]	50 randomly chosen images of persons in AR dataset	N/A	Sunglasses		Scarf	AR face database	80×88	AMM And LGBP,	2007
14				Session 1	0.84	1.00				
15				Session 2	0.80	0.96				
16	[24]	200	600	Not specified clearly			FERET AR and AT&T databases	N/A	LNMF and LFA	2005
17	[30]	100 persons chosen randomly 4 images/ person. of which one or two for training	4 images / person. of which one or two for testing	database used	# of training images 1	# of training images 2 /4	XM2VTS and AR database	96×96	N/A	2009
18				XM2VTS AR	88.3 79.5	96.8 with 2 training sample 91.5 with 4 training samples				
19	[29]	100 persons selected randomly four images for each person used	remaining used of testing	83.5%			XM2VTS and ORL	100×100	PDBNN, SVM and PCA	2008
20	[31]	1002 front view face images selected from training	FA has 1196 subjects and the FB set has 1195 subjects	97.41 %.			FERET database	48×54	KDA and LDA	2006
21	[26]	93	N/A	87.1%			AR Face database	18×25	N/A	2003
22	[42]	10 images of 37 individuals	10 images of 37 individuals	For CPCA & LPCA 72%, 47% on AR dataset 80%, 69% for the VISNET II face database			AR database VISNET II database	N/A	N/A	2008
23	[56]	100	300	~88-99% with different variations			AR data-base FERET	120×165	PCA and 2DPCA	2005
24	[38]	270	200	84-96% with certain variation due to expressions			AR face database	64×88	PCA, R-PCA, LNMF, AMM, face IT	2008
25	[15]	3 images /person training	10 images/ individual	99.5%			AR face database		PCA, MPCA, PPCA	2009
26	[32]	12 776	2 images /person out of 222	0.65-0.75%			AR-Face FRGC	N/A	N/A	2010
27	[34]	100-200	500-1100	85 - 95% and ~80% for scarf & sunglasses			AR face	120×170	PCA	2000

It catalogues the types of methods used, number of training and testing sets used, obtained recognition results, types of databases selected, image sizes, comparison with other methods (if any) and year of publication. This tabular form presents a clear and through collection of literature in one representation.

4. Conclusion

This survey deals with various methods that have tried to overcome the problem of partial occlusion. Many authors have worked on face recognition systems under controlled environments but with uncontrolled conditions less work has been focused. In this paper a classification is made among different methods i.e., parts based methods, fractals based methods and feature based methods particularly related to partial occlusion. Among them most of the work has been done on part based methods where the face image is divided into non-overlapping blocks and then analyzing the individual blocks using any parts based scheme. Similarly less work has been focused on fractal-based approach. Image misalignment is another new area of research where many loopholes are still to be handled. Regarding occlusion; since it's based on the appearance of image where the corresponding pixels are distorted, so part based methods are more effective. Also occlusion affects spatial domain of the image, so these methods are more appropriate. Further improvement that can be made when dealing with partial occlusion is that hybrid biometric capabilities can be used to enhance the performance. Since all the work done so far deal with 2D face recognition approaches, results can be improved further if 3D face recognitions techniques are employed to deal with partial occlusion.

Summarizing the overall methods, every technique has its pros and cons and each is effective in its own field of usage. Some schemes although become complex and their computational cost in terms of time and space may increase but trade-off is made on the functionality. Basically main emphasis of conducting this survey is to group together all the work related to partial occlusion in face images into one document. This effort gives an opportunity to other authors if they want to do more research in this regard.

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Aisha Azeem is a lecturer in University of Wah, Pakistan. She completed her BS and MS degrees from CIIT Wah in 2008 and 2011 respectively. Her research interests include digital image processing and software engineering.

Muhammad Sharif has been an assistant professor at Department of Computer Science, COMSATS Institute of Information Technology Pakistan. He holds PhD and has more than 18 years experience of teaching and research.

Mudassar Raza is an assistant professor at COMSATS Institute of Information Technology, Pakistan. He has more than seven years of experience of teaching undergraduate classes at CIIT Wah. He has been supervising final year projects to undergraduate students. His interest include are digital image processing, and parallel and distributed computing.

Marryam Murtaza She is currently a student of MSc in computer science at COMSATS Institute of Information Technology, Pakistan. she is working on her thesis. Her research interests include digital image processing and software engineering. She had completed her BSC in computer science degree from COMSATS Institute of Information Technology Wah in 2008.