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Face Recognition Practices for Partial Occlusion: A Survey

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Abstract
Over the years, biometrics has gained unparalleled popularity in digital medium and has proven its usefulness for several applications concerned with the threats and crime or security purposes. Face recognition is a widely emerging biometric for automating the surveillance, as it has aid in strengthening the security from several types of terrorist or criminal threats. However, there are several face recognition techniques which are categorized based on its error rates in recognition but there are few that gives the marginal rate for sufficient and validated recognition rates for occlude images. This survey illustrates the precise overview of the major face recognition techniques which paves strong foothold for the partially occlude images.

Keywords: *face recognition methods, feature extraction, partial occlusion, error in recognition rates*

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INTRODUCTION

Occlusion in context of facial imagery refers to the obstruction posed by wearable glasses, scarfs, hairs, or other accessories. Efforts made on face recognition under suitable condition has already been achieved in past studies but thus far the problems like illumination field, facial expression, pose estimation and partial occlusion has been the current concern of research for effective face recognition under varying condition. We have classified the literature in awe of the same issue and thus enlist the few of the effective attempts that have been made to resolve the issue.

These methods like Part Based Methods which comprises of methods like Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), Non-negative Matrix Factorization (NMF), Local Non-Negative Matrix Factorization (LNMF), Independent Component Analysis (ICA) and the other variations of it has shown better recognition rates. Also, other methods like feature-based method or fractal method usually considers the features around the essential facial parts like that of eyes, ears, or mouth region is incorporated in the recognition phase of this algorithm; though such methods show diverse set of analysis results. Occlusion is divided into two categories, i.e., natural occlusion and synthetic occlusion. Natural occlusion refers to the non-intentional blockade of view of the objects whereas the synthetic occlusion to the intently posing of artificial obstruction between the views. Partial occlusion sometimes severely affects the image processing of biometrics as it tends to disrupt the identification of the particular image. For example: in cases of retinal biometrics eyelashes occluded the iris, earrings might disfigured the earlobe and thereby inducing the error rates in the biometric recognition process [1]. Now, when it comes to the face recognition, there are several accessories that might be intentionally or unintentionally used to occlude the images [2]. Now, there have been significant rise in reports where the crime committer has posed disguised for which it fails the digital security system to detect and stop the threat at preliminary stages itself or even in situations where people change their look to trick the face recognition systems. These face recognition systems have failed completely in these criteria to overcome such difficulties [3].

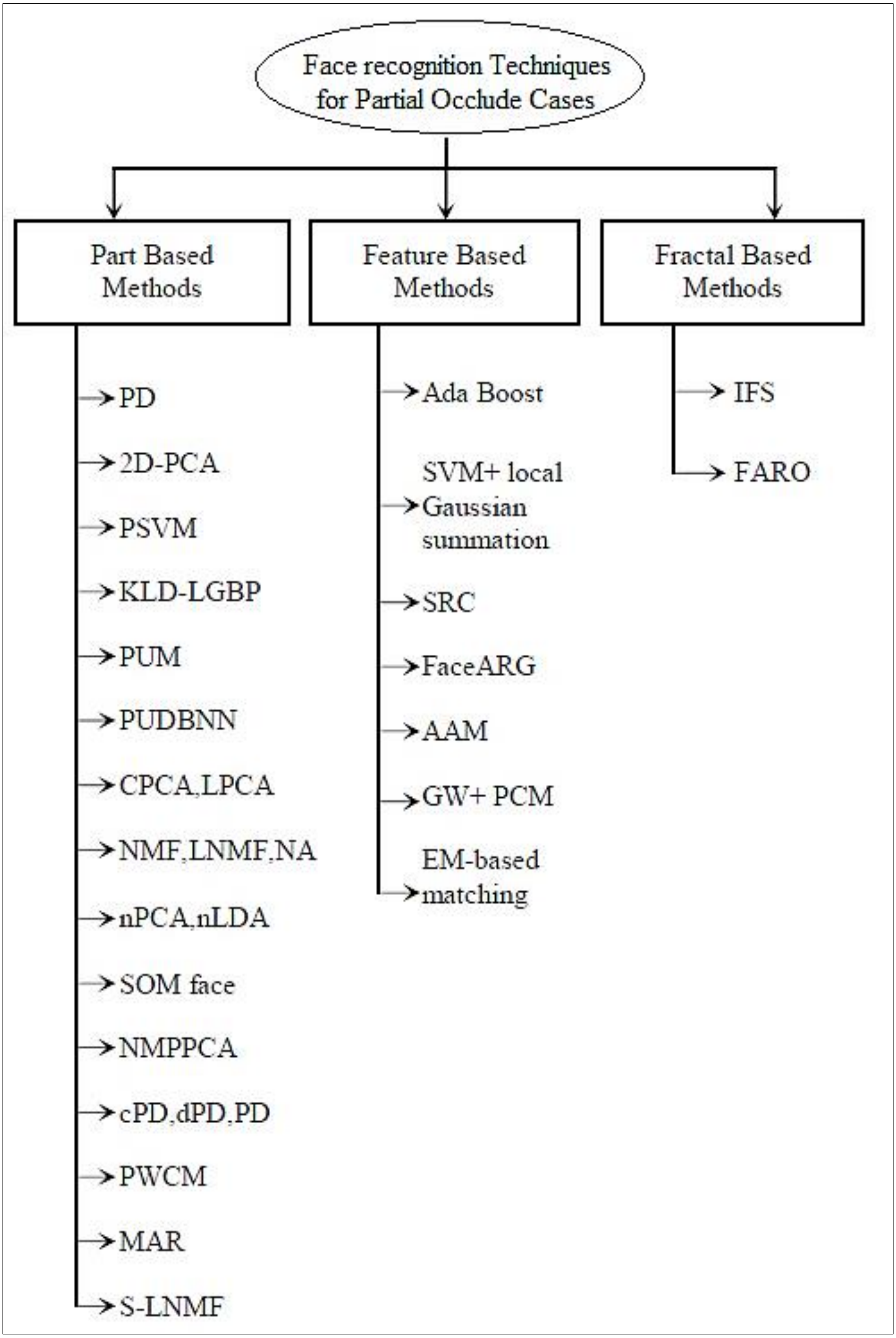

Fig. 1: *Enlisted Techniques for Face Recognition in Occlude Cases.*

Though the face recognition computer technology has achieved various feats but the problems of illumination, pose estimation, partial occlusion remain to be resolved fully with high accuracy in recognition rates [4–9]. Hence, there are few strategies adopted in the past studies to overcome the situation [10–15]. Methods like Principal Component Analysis (PCA) [16], Linear Discriminate Analysis (LDA) [17], neural networks [18] and several variations with the mix of them had been adopted to overcome this situations but none has proven its efficacy for the resolution of this conditional scenarios like non-linear cases as each has its own limitation of operations. There are other methods like Kernel machine-based Discriminate Analysis (KDA) [19], neural networks [20], Flexible Discriminate Analysis (FDA) [21] and Generalized Discriminate Analysis (GDA) [22], which are suitable for non-linear cases but haven't grown in application because of its high computational cost of operation for both training and testing of datasets. The face recognition method basically relies on two feature sets, i.e., global and local features [23, 24]. These features are easily influenced by occlusions or noises of certain types and thereby degrading the robustness of such methods. There are studies which report the high effectiveness of local features when employed for face recognition [25–29]; but at the same time these features are mostly prone to the affects by partial occlusion. However, if used intelligibly, such methods show remarkable results.

Attempts made by Martinez which employs his robust recognition system by merging the local features based on similarities [30]; or of the attempts on Support Vector Machines (SVM) classified the local features into groups that deal with the features of facial parts like eyes, ear, nose to establish a geometrical interpretation of corresponding feature sets [31–33]. Now, there are other categories of face recognition which focuses more on the holistic features of facial regions, i.e., relying on global features. Thus, in the following section we present the review of acknowledgeable methods which cite better results in performance test specifically for partially occlude images.

FACE RECOGNITION FOR PARTIAL OCCLUSION

The primary methods till now for resolving the issue of partial occlusion is divided into three classes namely: Feature-based methods, Part-based methods and Fractal-based methods (Figure 1).

Part-Based Methods

Part-based method comprises of several bits of process which involves the division of facial image into several overlapping and non-overlapping pixel sets which are then used for the matching task [34]. Tan *et al.* had presented a concept of eliminating the non-matching details from the non-parametric partial similarity between two sets of facial images; which helps in extracting interpersonal details [35]. Here, the test and training image separated into blocks and then stick-out to form a self-organizing map (SOM); these maps in the partial neighboring distances and subsequently helps out in automatically finding the most similar parts between the two images. This method is also named as non-metric distance measure due to the fact that it doesn't satisfy the self-similarity of other metric properties like triangular inequality. Thus, distance measure involved in the method is compared with other distance measures, for example: Simplified Mahalanobis (SM), Modified Squared Euclidean distance (SE), Weighted Angle-based distance (WA) and Angle-based Distance between whitened feature vectors [36]. The experiment had carried out over the AR face database and ORL database [37]; on both database the recognition rates (RR) of 97 and 74.6% respectively had reported. In another work by Kim *et al.* 2D-PCA method were used to handle the problem of partial occlusion [38]. This method relies over K-NN and 1-NN classifiers which enables it to eliminate the occlude parts and check for partial similarity. Thereafter several attempts in combination with supervised and unsupervised training had been carried out with these classifiers. The method shows some approximate recognition efficiency of 98 and 99% for sunglasses and scarf respectively. Jia and Martinez employs SVM as a classifiers which was modified for missing features in the occlude region of facial imagery [39]. This experiment is conducted over AR face database and Face Recognition Grand Challenge (FRGC) datasets [40]. For facial images with varying facial expression and partially occlude images, a probabilistic method was attempted [41]. For this, the computing region of facial images is subdivided into k-regions and then each region is analyzed using Mahalanobis distance; which orderly gives a performance range of 75-88% recognition results. Similarly, Local Gabor Binary Pattern (LGBP) is used in combination with Kullback-Leibler Divergence (KLD) to measure the probability for the same case [42]. The LGBP method forms the multi-scaled images followed by merging of local component to form up a single global feature vector from the histogram of each of its components. A very similar effort by Wang *et al.* and Meng *et al.* use global part detectors by Help of Oriented Gradients (HOG) and Local Binary Pattern (LBP) and develop Gabor feature-based Robust Representation and Classification (GRRC) system [43–50]. Latter, Local Salient (LS-ICA) technique was introduced which employs ICA architecture in order to determine the local basis of facial image [51]. There were instances where the method was compared with Local Non-Negative Matrix factorization (LNMF) and local feature Analysis (LFA). In his methodology the regions of facial imagery with special features like eyes, nose, lips etc., are retained and latter aligned in orderly fashion for the recognition process. There was another method which uses Posterior Union Model (PUM) and the measure of similarity is determined within the class containing samples per class [52]. They have also tried overcoming the difficulty of large feature vectors from single training image. The recognition sampling performed over XM2VTS and AR databases gives the performance of 98.8 and 91.5% respectively. Thereupon, a Probabilistic Decision Based Network (PDBNN) approach for occlude faces in combination with PUM is introduced; where the main focus is on increasing the robustness of the system by emphasizing on the matched features [53]. This method is tested on XM2VTS & ORL face datasets with the performance of 84.4 and 83.5% of recognition rates, respectively. In an attempt the feature vector dependent on the sets of similarities are formed on the test and probe images [54]. Followed by it, the LDA technique is employed as a classifier for separating distinguished classes with 97.41% of recognition rates over FERET database. There are also few methods which follow learning-based approach using neural network or fuzzy scaling as feature classifiers. Among such methods most notable is the Auto-Associative Neural Network for face reconstruction; here the classifier used has three layer multilayer perceptron to evoke original face from distorted ones [55]. Experiments carried over AR datasets with 93 images for pixel wise training of size equivalent to 18 x 25 pixels.

Lately, three variants of PCA methods has proved its effectiveness against recognizing occlude images [56]. The methods are as follows:

(1) Component based PCA (CPCA), wherein different components of the facial features are handled separately.
(2) Holistic method, where the complete facial region is converted into sub-spaces [57, 58]. In this method, subspace learning is implemented or weighted factors are assigned to distinct regional spaces over the facial imagery. Though the algorithm can perform effectively when only the 20% of the face is occluded. Since, it is based on reconstruction of the image by accounting the difference of misalignment from the reconstructed image.
(3) Lophoscopic PCA (LPCA), where only those regions are separately identified where the chances of occlusion are likely to occur [59]. Though it increases the performance but its major drawback is the high computational cost.

Following such tasks, a fusion mechanism is used to find the decision sets of spate classes of each image belongs to; this methods gives 72, 69 and 47% of recognition rates for the above mentioned AR database. There comparison with other methods namely ICA, LNMF, NMF and Neural Associators (NA) was studied in [60]. The studies has also been attempted towards the handling of expressions based on LDA & PCA methods; followed by normalization of grey intensity levels through mean variance and histogram equalization to eliminate the effects of illumination and partial occlusion [61]. In all of this methods, there was an assumption taken in advance before experimenting that the given image is occluded and the reference image is available with the probe image being locally occluded under the condition of partial similarity [62, 63]. For Selective Local Non-Negative Matrix Factorization (S-LNMF) based method relies over divided PCA and 1 NN classifier employed to detect distortions, where LNMF was used for comparison over the same AR face recognition datasets cropped to 64 x 88 pixel sets [64]. A face recognition method in PCA category for addressing the illumination problem using a localized non-linear feature selection method is claimed to be robust in varying light reflectance fields and partial occlusions [65]. For this method kernel-eignspace is used for feature extraction with merging of neighboring sub-parts in phase congruency with respect to the reference image. This accounts for an overall performance of 99.5% on AR datasets.

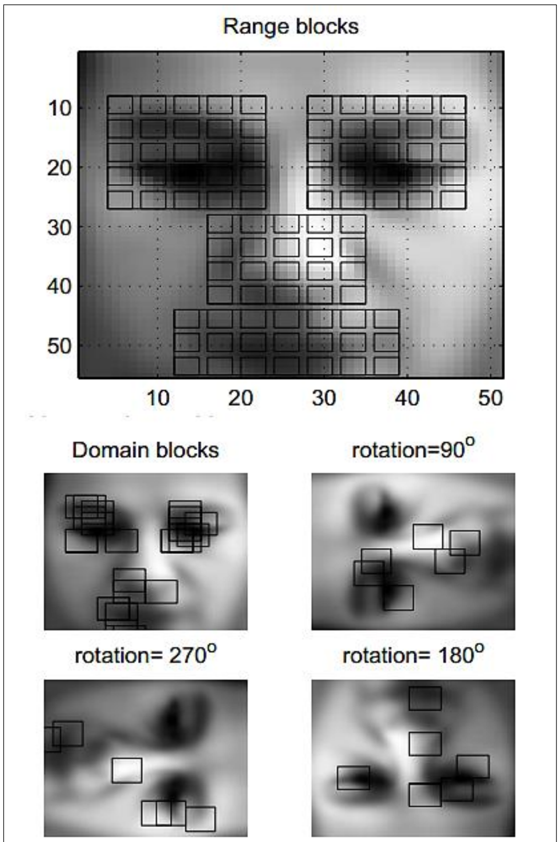

Fig. 2: *Range Block for Major Detected Subfractal Areas (Eyes, Nose, Mouth, etc.) for an Arbitrary Image and That of with Rotation.*

Fractal-Based Methods

Partitioned Iterated Function System (PIFS) based face recognition presented an algorithm computing self-similarities between the given image subspaces and the simultaneously establishing the relationship between several squared grid regions of the facial imagery (as shown in Figure 2) [66]. Due to its sensitiveness towards occlusions it is handled locally handled locally and thereby further distortions are eliminated through ad-hoc distance measure. There are only a handful of major works attempted with this type of method. The experiments carried over AR face database show dissimilar results [67]. In this type of method, the image is preprocessed and resized to have the fixed dimension while ensuring the eyes and mouth are centric with respect to the time; thereafter the number of sub spaces is accessed iteratively. Other similar methods are outlined in Ref. [68].

Feature-based Methods

Feature based methods takes consideration of individual features like eyes, mouth, eyebrows, nose in account for the recognition process and ignores the other features [69]. Since the probability is measured to find the correct image; consequently, it deals with imprecise location and partial occlusions [70]. In this type of method, the image is divided into distinct local parts and these parts are then analyzed in isolation with the Eigenspaces.

This allows the learning of alignment of subspaces in the controlled lighting environment or occlusion. The experiment is carried over the A facial datasets for 100 grayscale images corresponding to 50 men and 50 women of size 120 x 170 pixels; giving the recognition rate of a range around 85-95% and ~80% for scarf occluded and sunglasses occluded images respectively. Other similar attempts are illustrated in Ref. [71]; wherein in this method soft masking is used as a primary processing tool to classify the outliner in occlusion images. Experiments over MIT face recognition database gives the performance estimate of 95%. The graph-based technique where facial imagery is reconstructed using graph model with label learning approach is a hot research topic [72]. This method uses sparse representation and graphical model for recognition of partially occlude images. Notably, an illustrative example of such methods is Active Appearance Models (AAM) which builds a mesh-like structure over the facial imagery in order to mark visible distinctive features of the facial region. In the past, this method is attempted with adaptive fitting strategy over several databases which give the high performance range for images 10-40% partially occlude [73]. This method has an upper hand over the previously cited methods as the simple image can be occlude by facial hair or hands thus by assigning the adaptive features with graph modeling is a great job in this direction.

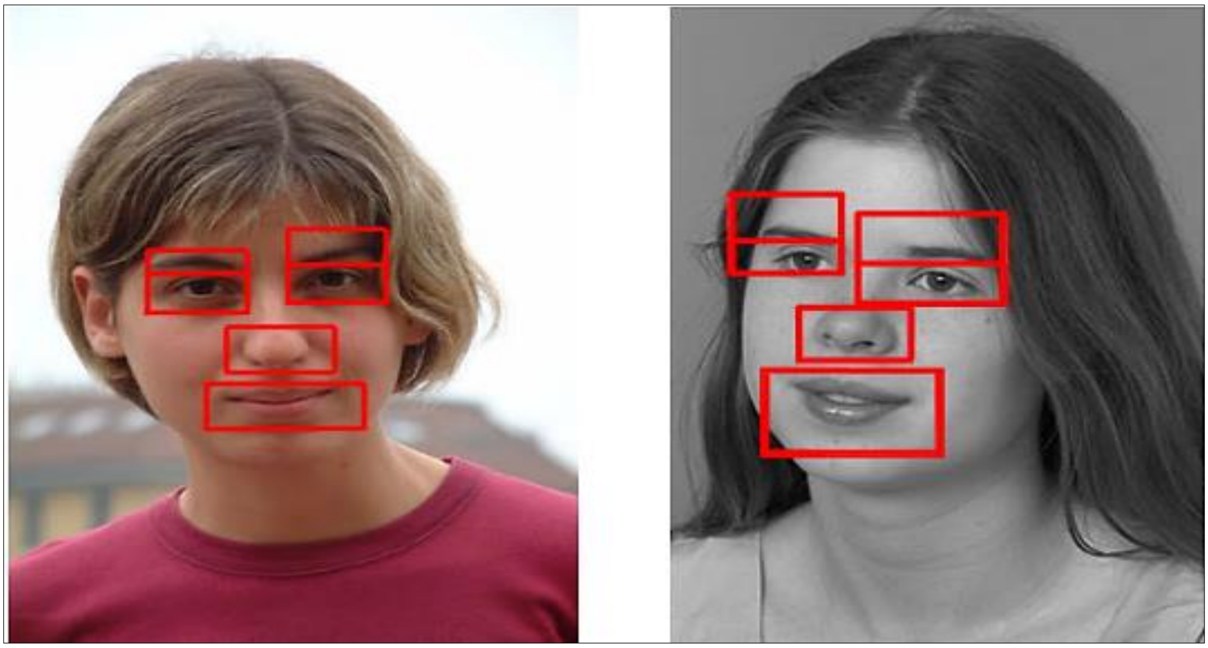

Fig. 3: *Feature Division Results on Frontal and Rotated Imagery of Facial Regions.*

Table 1: *Various Methods of the Researchers for Resolving the Issue of Partial Occlusion and the Aforesaid Mentioned Techniques.*

S.No.	Methods	Training Sets	Testing Sets	Recognition Results (%)	Publication Year
1	Ref. [35]	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	2006
2	Ref. [38]	35 sunglass images and 35 scarf images of 20 men and 15 women	100 sunglass images and 100 scarf images for testing	96.00%	2007
3	Ref. [39]	1,200 images from AR and 800 images from FRGC	N/A	88.9%	2009
4	Ref. [41]	50 randomly chosen images of persons in AR dataset	Remaining used for testing	75-85%	2002
5	Ref. [42]	50 randomly chosen images of persons in AR dataset	N/A	75%	2007
6	Ref. [51]	200	600	88.3%	2005
7	Ref. [78]	100 persons chosen randomly 4 images/person of which one or two for training	4 images/person. of which one or two for testing	83.5%	2009
8	Ref. [53]	100 persons selected randomly four images for each person used	Remaining used of testing	97.41 %.	2008
9	Ref. [54]	1,002 front view face images selected from training	FA has 1,196 subjects and the FB set has 1,195 subjects	87.1%	2006
10	Ref. [55]	93	N/A	72%	2003
11	Ref. [56]	10 images of 37 individuals	10 images of 37 individuals	~88-99% with different variations	2008
12	Ref. [63]	100	300	84-96% with certain variation due to expressions	2005
13	Ref. [64]	270	200	85-95% and ~80% for scarf & sunglasses	2008

In terms of adaptability, this graph-mesh based approach is implemented with other adaptive algorithm like SVM (Support Vector Machine) in combination to deal with the local distortion features [74–76]. The advantage of this method is that it satisfies Mercer's theorem which other have failed to. Since, the errors formed by occlusion are generally sparse in nature and didn't affect the pixels in an adversely. Thus, the performance range of such methods is effective. Since occlusion or errors are sparse in nature so they do not usually affect the pixels greatly. Performance on various databases shows that algorithm executes effectively.

DISCUSSION

After reviewing different principal methods in the literature of face recognition for partial occlude images, it can be concluded that most of the work is done under part-based methods, though the attempts which are based on feature based methods show promises to bring better results in the near future.

The part based methods usually converts the image into subspaces and then try overlapping with the matching images for finding the better probability of matching with several subspace reduction technique [77]. Whereas those methods which belong to the feature-based models include Ada-Boost and SVM based methodologies using Gaussian mixtures or eignspaces. Like already stated in the above text, none of the method handles all the problems effectively in the race of robust face recognition system.

The various methods of the researchers for resolving the issue of partial occlusion has been discussed and the aforesaid mentioned techniques are summed up in the Table 1. On summarizing, the overall techniques have their pros and cons and variant field of usage.

Some schemes become complex but give better results but it increases the hardness of computation and making the system functionally complex is highly undesirable within the similar trade-off. Our effort of grouping all the literature within a single document will let the researchers to have an opportunity to gauge their research accomplishments with that of the more required to furnish in the literature within this regard.

CONCLUSION

This literature survey deals with various methods that overcome the problem of occlude images under uncontrolled conditions, thought there are attempts which perform effectively for controlled conditions but in the pursuit to make the system highly robust and adaptive is required to make the attempt under the uncontrolled condition which is way challenging than the former. In this paper, we have classified the face recognition techniques into three parts. The least amount of work has been done over the fractal based approach whereas the feature based approach promises to eliminate several loopholes in the partial occlusion imagery to give better results in the near future. However, it has also comprises of less amount of contribution in the literature. Since, the occlusion is associated with corresponding distorted pixels and for this, part-based method has proven to be more effective it seems that the field is saturating within this region. 3D face recognition is effective though it has higher computational complexity which is undesirable for a simple real-time application.

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