Computer Vision based Detection of Partially Occluded Faces

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Abstract: ***In today's world, security has gained utmost significance in every walk of life. With the recent advancements in image and video analytics, emphasis has been towards developing enhanced surveillance systems which perform complex tasks that include automated security incident detection, tracking and analysis in real time. The primary objective of this paper is to automatically detect the presence of any masked or occluded face in real time. A robust technique based on pivotal facial points has been developed. The paper discusses in detail how the pivotal points are observed extracted are used in discovering masked faces in real time. Analysis of this algorithm's performance on test data sets gives positive insights for further enhancements towards occluded face detection in real time surveillance.***

Keywords: Mask detection; face detection; eye detection; face occlusion; video surveillance; partial occlusion

I. INTRODUCTION

Occlusion in image and video processing refers to the scenario where there is an obstruction posed in viewing an object. Occlusion may be complete or may be partial based on the visibility of the object. Detecting occluded faces is one of the key challenges in real time video sequences and is the most significant challenge in the case of surveillance systems. Occlusion of faces may be natural or may be intentional. Some examples of natural occlusion are faces being hidden when two persons cross each other, person walking away from the camera showing his back, face hidden behind a moving object etc. Intentional occlusion includes hiding of face purposefully using a mask or any other object such as books or paper or cases where a person intentionally hides the face with hands.

While natural occlusion is not of much significance, identifying intentionally occluded faces are of highest significance in case of surveillance systems[12][13] deployed for security purposes in Banks, hospitals, ATMs, Airports etc,. Several approaches have been proposed for occluded face recognition.

Approaches to solve occlusion can be categorized into three types based on the methods employed to classify occlusion namely part based methods, feature based methods[15][16] and fractal based methods. Figure 1 depicts the different approaches used to address the problem of partial occlusion.

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II. LITERATURE REVIEW

Several face recognition systems which deploy different approaches to recognizing faces have been developed over the years. These works were primarily focused towards detecting and identifying faces in a give image or video and in turn be used to study various emotions, facial gestures and behavior [14]. Table 1 shows some of the previous works performed over occluded face recognition.

III. DEFINING AN OCCLUDED FACE

In general, human tends to have similar facial features that are used to describe the face of a person. These features include a couple of eyes, eyebrows, nose, mouth etc. The location and shape of the organ is predominantly same for most persons. When any of these organs is hidden completely or partially, we can understand that the face is not completely visible leading to an occluded face. Some simple examples of partially occluded faces are hiding the eyes using dark sun glasses, covering the face using some kind of masks etc.

The first two images in figure 2 shows some examples for normal faces while the other two shows occluded faces. Such occluded faces must be clearly identifiable by a smart security system and an automated alert should be triggered as soon as an occluded face is detected.

IV. PROPOSED APPROACH

Detecting partially and completely occluded faces involves training the security system to extract the features from the image. The principal components that describe the features are extracted using PCA. The smart system is trained with samples of different types of facial occlusions using the various sample images available in the training database. In addition to this conventional training, a new approach to detect pivotal points in face is included. The primary advantage of the pivotal point approach is that it can easily check if all the pivotal points are visible in a given input source rather than performing a complete pattern matching or feature matching with the trained data. Figure 3 shows the seven pivotal points that are considered pertaining to a normal human face.The pivotal points are categorized as fundamental pivotal points and derived pivotal points. Fundamental pivotal points are those points which are observed directly from the video frame and do not require any computation. From the above figure it can be seen that the Left and right eye pupil, nose tip and mouth center can be extracted by directly observing the video frame sequence and hence constitute fundamental pivotal points (Points 1 to 4 in figure). The intersecting points of the perpendicular line drawn through the eye pupils and the horizontal line drawn through the nose tip are considered as right and left cheek point respectively (Points 5 and 6). The forehead point is computed as the intersection of two lines drawn at an angle of 45 degrees from the left and right eye pupil respectively. Since these three points (points 5 to 7) are computed using other feature points, these are considered as derived feature points. Figure 4 illustrates how the derived pivotal points are computed using the fundamental pivotal points. Based on the depicted pivotal point computation and deducing the derived pivotal points from the fundamental points, these points are marked in the given frame containing the face of a person.

Figure 5 shows the plotting of pivotal points are plotted over a real time image using the logic explained in the earlier figures. The image files along with the pivotal point details are given as input to the classifier. The classifier uses binary Support Vector Machines (SVM) to classify whether the given face is occluded or not. Figure 6 shows the block diagram of the proposed system.

Feature Extraction is the initial step which is concerned with extracting the essential details pertaining to the given input. Prior to feature extraction step, the conventional pre-processing and filtering steps are performed to enhance the image quality as per the need of the system. Facial features include extracting regions specific to eyes, nose, mouth etc, from the given image and storing them as a feature vector for computational ease. Assume X to be the feature vector, the features pertaining to the pivotal points x1 to x7 constitutes the elements of the feature vector. These facial features are extracted using Viola-Jones Algorithm.

Dimensionality Reduction is the next step that follows feature extraction. As discussed earlier each feature is described using several dimensions. However, not all dimensions are significantly needed to describe about the particular feature. A subset of the dimensions alone is sufficient to describe the feature. This process of representing a feature with minimal dimensions or a subset of actual dimensions is called dimensionality reduction. From a theoretical stand point, increasing the number of dimensions should ideally increase the performance. However, more dimensions results in performance degradation. This is known as curse of dimensionality. Assuming that there are n training samples, each having dimensionality d, the time complexity is O(nd2). This implies that as the dimensionality increases the time complexity increases exponentially. This substantiates the need for dimensionality reduction. Also, reduced parameters representing the dimensionality means that the storage space is reduced resulting in reduced space complexity as well. Some common methods to perform dimensionality reduction are Principal component Analysis (PCA), Fisher Linear Discriminant and Singular Value Decomposition (SVD). Of these methods, the proposed approach employs Principal Component Analysis (PCA) for dimensionality Reduction.

Principal Component Analysis identifies a set of attributes less than the actual set and uses the reduced set of attributes to represent the feature. These new set of attributes are called principal components. The essential properties of these components are that each component is unique in nature and the principal components are uncorrelated. PCA ensures that the data is projected along the directions where there is a maximal data variation. These directions are determined by the Eigen vectors of the covariance matrix which corresponds to the largest eigen values.

Assume that the feature vector is X and comprises of n dimensions. These n dimensions have to be reduced k dimensions such that k < n.

$X = \{x_1, x_2, x_3, \ldots, x_n\}$

Each x_i has d dimensions. The first step is to determine the sample mean.

$$\mu' = (1/n)\sum_{i=1}^{n} x_i$$

This is followed by computing the difference between the sample mean and the data point.

$$z_i = x_i - \mu'$$

The third step involves computing the scatter matrix

$$S = \sum_{i=1}^{n} z_i z_i^t$$

The next step is to compute the eigen vectors $e_1, e_2, e_3, \ldots,$ e_k corresponding to the k largest eigen values of S. Now the Eigen Matrix E is computed such that

$$E = [e_1, e_2, \ldots\ldots\ldots\ldots\ldots, e_k]$$

Finally, the closest approximation to X is chosen as the best fit model Y.

$$Y = E^t . Z$$

The next step towards occlusion detection is to observe the pivotal points from the input image. As discussed earlier, the pivotal points are classified as Fundamental and Derived Pivotal points. The pivotal points are passed as input to the classifier. The classifier is trained to identify the frontal face as well as tilted face. The classification mechanism using pivotal points is illustrated in the flow diagram shown in Figure 7.

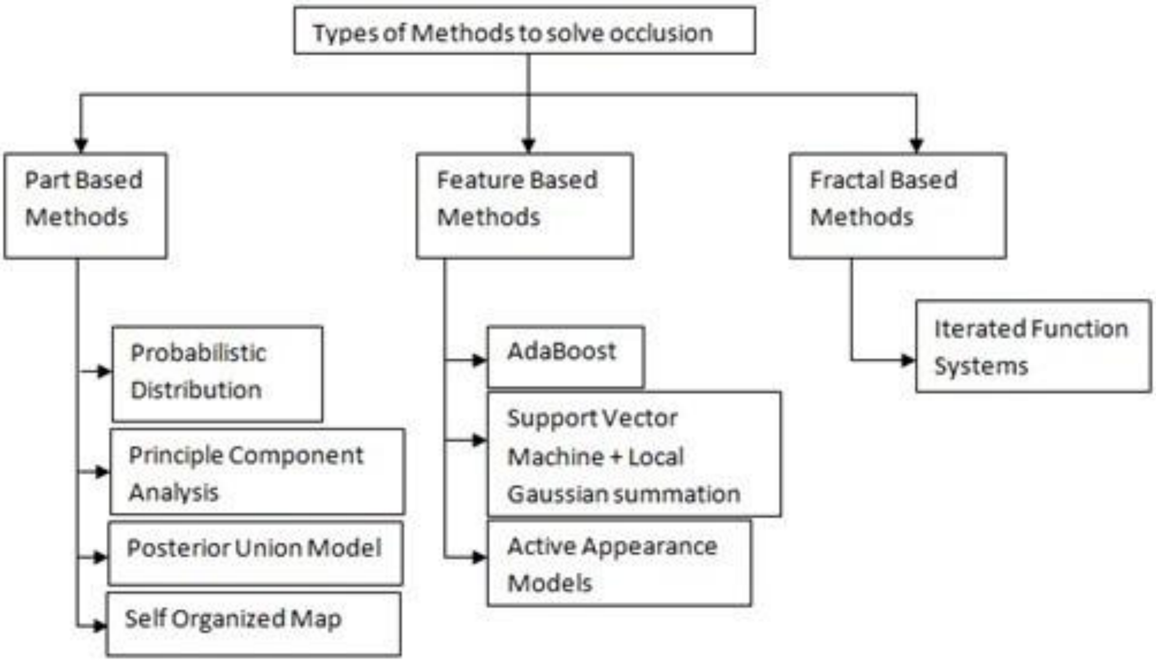

Fig. 1. Various approaches to solve the problem of occlusion

Fig. 2. Examples for normal and partially occluded faces

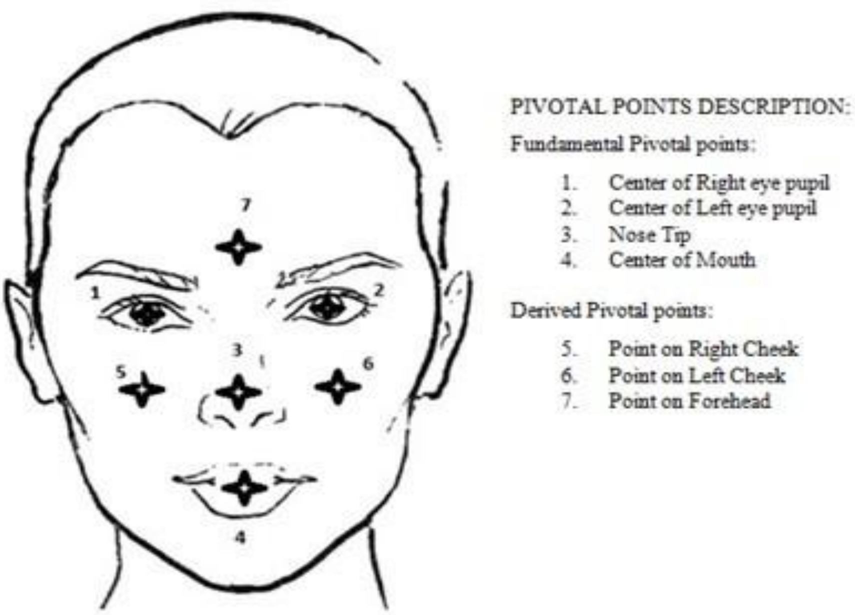

Fig. 3. Pivotal points and its description

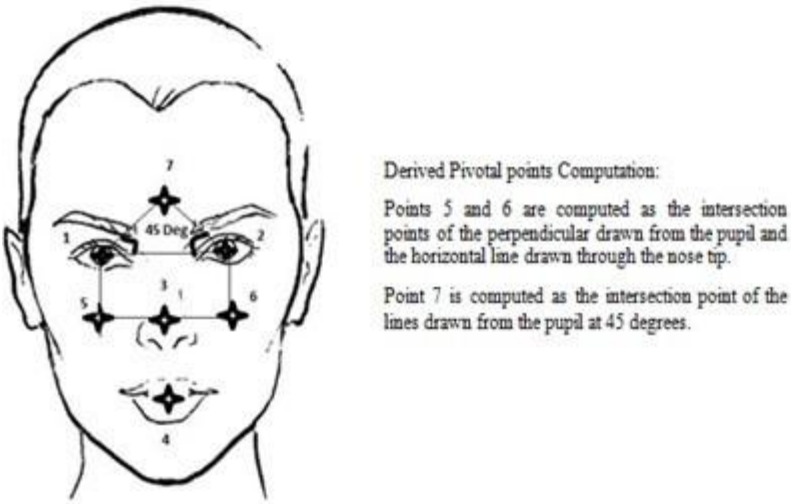

Fig. 4. Derived computing points description and plotting

Fig. 5. Pivotal points plotted in real time images

Table- I: Few works towards occluded face detection

Reference Number	Author	Work done
[1]	Ibrahim Venkat et.al.	The proposed face recognition system takes into consideration the psychophysical features of face and uses the same to detect occlusions.
[2]	Kohtaro Ohba and Katsushi Ikeuchi	The proposed face recognition system uses eigen vectors to detect partially occluded faces.
[3]	Yongbin Zhang and Aleix M. Martinez	The proposed face recognition system uses weighted average score and compares it with the matching scores of the local images.
[4]	Aleix M. Martinez	The proposed face recognition system localizes the face into discrete parts and part based local representation approach is followed.
[5]	Xiaoyang Tan et. al.	The proposed face recognition system uses a local probabilistic method along with a self organized map (SOM). This system responds well to partial occlusions and facial expression changes.
[6]	Ping-Han Lee et. al.	This system is built around a technique which selects the best set of features of an individual and uses them to boost the face recognition pertaining to the individual.
[7]	Kazuhiro Hotta	This approach uses Support Vector Machine (SVM) along with local Gaussian summation to identify partial occlusion.
[8]	John Wright et. al.	This approach considers sparse errors due to occlusion along with the training images. These sparse errors have been handled with standard pixel basis.
[9]	Xiaoyang Tan et. al.	A new method which deploys perception based non-metric partial similarity is used handle partial occlusion.
[10]	Yu Chen et. al.	This system maintains the locality specific features to recognize faces

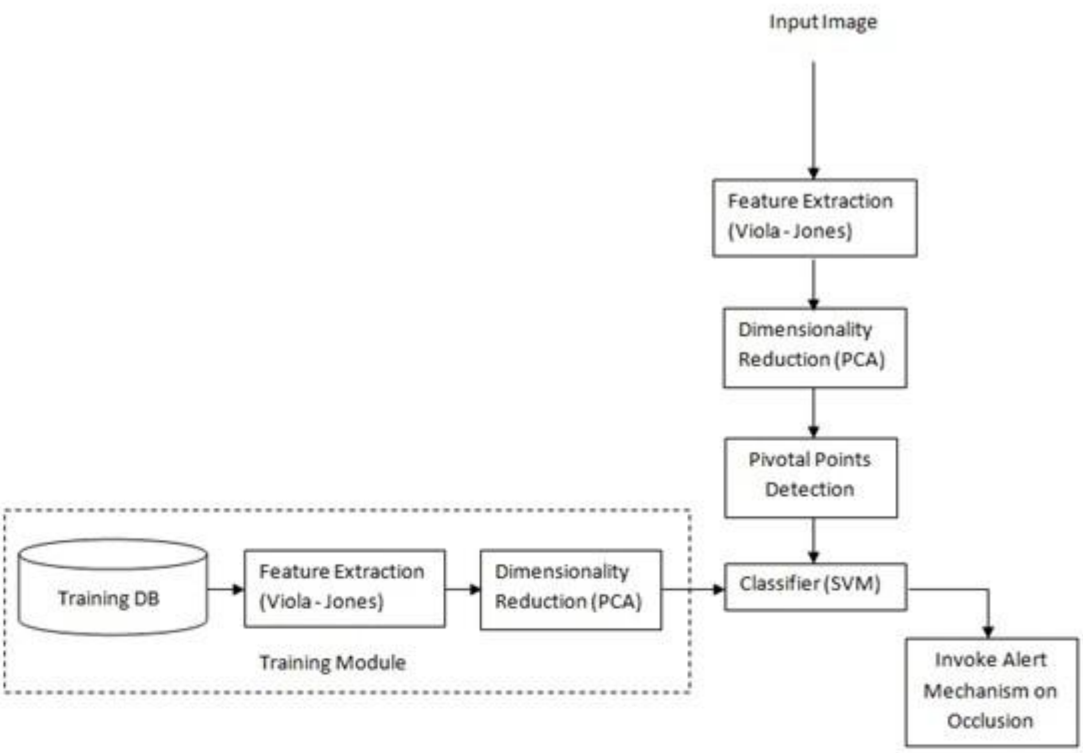

Fig. 6. Block diagram of proposed system

If the input image is classified as Frontal face, then the four fundamental pivotal points are extracted which is followed by computation of derived pivotal points. The system then checks if all the seven pivotal points are visible. If any of these pivotal points is not visible, the system concludes that the face is occluded.

If the input image is classified as tilted face, then the skin texture is extracted and checked with the trained set. In the case of tilted images, the region around derived points 5 and 6 are considered and a texture analysis is performed. The texture observed around this region is compared with the threshold levels of the skin and a conclusion is made if the face is partially occluded or not. Once the system detects any occluded face, an alert message or warning is generated and this in turn triggers the automated alert system.

The primary advantage of this approach over the region based approaches or part based approaches is that, the entire face is not considered for manipulation which in turn reduces the processing time and enables faster decision-making and instantaneous triggering of alerts when a partially occluded image is given.

V. EXPERIMENTAL SETUP

The code pertaining to the experiment was developed using Matlab and the images for testing were taken from AR Face Database [11]. The AR Face Database is a commonly used Face Database which comprises of partially occluded images. The partial occlusions are provided by covering the eyes with dark sun glasses and the mouth with scarf.

The AR Database comprises of close to 2500 images in all. Also, a set of 150 real time images captured with frontal view and tilted view has been used for testing the experiment. The Matlab code was executed and the results indicate very high recognition rate in case of partially occluded faces.

The parameters that were used to evaluate the performance of the system are true positive rate (TPR), false positive rate (FPR), false negative rate (FNR), relative operating characteristic (ROC) curve and accuracy measured in terms of Correct Identification Rate (CIR).

1) True Positive Rate (TPR): This represents the percentage of normal faces identified as normal by the system. For a robust system, the TPR value should be higher. This is otherwise called as Sensitivity.

True Positive Rate (TPR) = True Positive / (True Positive + False Negative)

2) True Negative Rate (TNR): This represents the percentage of occluded faces identified as occluded by the system. For a robust system, the TNR value should also be higher. This is otherwise called as Specificity.

True Negative Rate (TNR) = True Negative / (True Negative + False Positive)

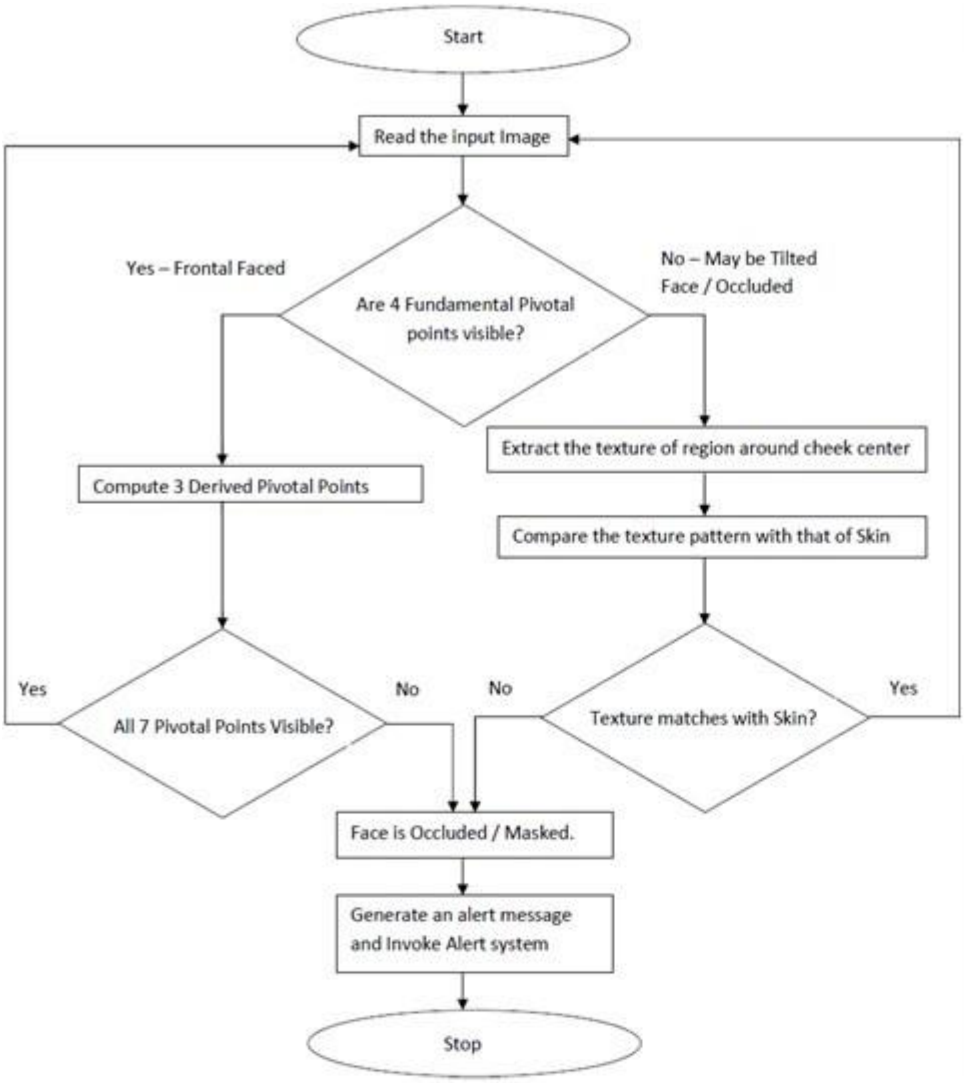

Fig. 7. Flow diagram for theproposed approach

3) False Positive Rate (FPR): It is the percentage of occluded faces that have been accepted as normal faces by the system. This metric in turn reflects the incorrect classification made by the system. The system can be termed as robust if this FPR is lower given by:

False Positive Rate (FPR) = 1 – Specificity

4) False Negative Rate (FNR): It is the percentage of normal faces getting classified as occluded by the system. FNR is directly proportional to misclassification of normal faces as occluded. For the system to be robust the value of False Negative Rate should be minimal.

False Negative Rate (FNR) = 1 – Sensitivity

5) Receiver Operating Characteristic (ROC): Receiver Operating Characteristic (ROC) plot is a graph which is used provide a measure of the tradeoff between FPR and FNR. The matching decisions pertaining to the system are taken based on a threshold (Th).

6) Correct Identification Rate (CIR): Correct Identification Rate is given by the percentage of successful classification performed over the total number of given images that are queried or classified

Correct Identification Rate (CIR) = (Number of successful classification / Total Images Queried) * 100

VI. EXPERIMENTAL RESULTS

The proposed approach was tested with AR face database [11] which comprises of more than 2000 images of 100 subjects. These images are of different nature and taken under different conditions such as various facial expressions, different effects due to illumination and occlusions. These occlusions may be due to wearing of sun glasses or may be due to wearing scarf. The proposed system performance was measured against the performance metrics mentioned in the previous section. Results indicate a very good degree of accuracy percentage. A set of 1000 images comprising a mixture of 300 normal facial images, 400 sun-glassed facial images and 300 images with scarf were used to train the system. A sample set of 700 images from AR Face database comprising a mixture of normal images, images with sunglasses and images with scarf were selected and tested with the proposed approach. Also, another set containing 1000 real time images were tested. Table 2 lists the accuracy percentage for each class of images. Figure 8 shows some of the sample images in AR Face dataset. Figure 9 shows the classification for the three different types of images considered. The proposed approach was also tested using AR Face Database. Table 3 lists the accuracy percentage results for AR Face database.

From the previous table it can be seen that the accuracy percentage for all classes is above 97% when tested using AR Face database. Figure 10 shows the plot for classification of images using AR face database.

A. Confusion Matrix

Confusion matrix is used to describe the performance of the classifier model that is created and whose true values are known. In this case, there are three known classes namely normal images, images with sun-glasses and images with face partially covered by a scarf. The class names are given as Normal, Sun Glass and Scarf respectively. All the true positive values will be entered along the leading diagonal of the matrix constructed while the misclassification entries will be marked in the respective blocks. Table 4 shows the confusion matrix generated for the test done with images taken from AR face database[11] and the confusion matrix pertaining to the test done with real time image set discussed in the previous section is depicted in table 5.

From table 4, which is the confusion matrix for AR Face database, various metrics such as accuracy, misclassification rate, true positive rate, false positive rate, specificity, precision, prevailance etc can be computed as follows:

True Positive $_{(Normal)}$ *=469 True Positive* $_{(Sunglass)}$ *=102 True Positive* $_{(Scarf)}$ *= 112 True Negative* $_{(Normal)}$ *=218 True Negative* $_{(Sunglass)}$ *=586 True Negative* $_{(Scarf)}$ *=579*

False Positive $_{(Normal)}$ *= (1+1) = 2 False Positive* $_{(Sunglass)}$ *= (7+2) = 9 False Positive* $_{(Scarf)}$ *= (4+2) = 6 False Negative* $_{(Normal)}$ *= (7+4) = 11 False Negative* $_{(Sunglass)}$ *= (1+2) = 3 False Negative* $_{(Scarf)}$ *= (1+2) = 3*

Precision $_{(Normal)}$ *= 469/(469+1+1) = 0.9957 Precision* $_{(Sunglass)}$ *= 102/(102+7+2) = 0.9189 Precision* $_{(Scarf)}$ *= 112/(112+4+2) =0.9491*

Recall / Sensitivity / TPR $_{(Normal)}$ *= (469/480) =0.977 Recall / Sensitivity / TPR* $_{(Sunglass)}$ *= (102/105) =0.971 Recall / Sensitivity / TPR* $_{(Scarf)}$ *= (112/115) =0.974 Specificity / TNR* $_{(Normal)}$ *=218/(218+1+1) = 0.9909 Specificity / TNR* $_{(Sunglass)}$ *=586/(586+7+2) =0.9848 Specificity / TNR* $_{(Scarf)}$ *=579/(579+4+2) =0.9897 Misclassification Rate* $_{(Normal)}$ *= (11/480) = 0.023 Misclassification Rate* $_{(Sunglass)}$ *= (3/105) = 0.028 Misclassification Rate* $_{(Scarf)}$ *= (3/115) = 0.026 Overall Accuracy = ((469+102+112)/700) = 0.9757*

Based on the above computations, the performance metrics of the proposed approach with respect to AR Face Database is shown in table 6. Figure 11 strikes a clear comparison between the true positive rate and misclassification rate for the proposed approach when tested with AR Face Database. It can be observed that the sensitivity and specificity values are way too high when compared to the misclassification rate which is very negligible. This suggests that the system is highly accurate with its classification results.

From table 5, which is the confusion matrix for real time dataset, the following metrics have be computed below and tabulated in table 7.

True Positive $_{(Normal)}$ *=691 True Positive* $_{(Sunglass)}$ *=148 True Positive* $_{(Scarf)}$ *= 141 True Negative* $_{(Normal)}$ *=293 True Negative* $_{(Sunglass)}$ *=839 True Negative* $_{(Scarf)}$ *=848*

False Positive $_{(Normal)}$ *= (4+3) = 7 False Positive* $_{(Sunglass)}$ *= (5+1) = 6 False Positive* $_{(Scarf)}$ *= (4+3) = 7 False Negative* $_{(Normal)}$ *= (5+4) = 9 False Negative* $_{(Sunglass)}$ *= (4+3) = 7 False Negative* $_{(Scarf)}$ *= (3+1) = 4*

Precision $_{(Normal)}$ *= 691/(691+4+3) = 0.9899 Precision* $_{(Sunglass)}$ *= 148/(148+4+2) = 0.9610 Precision* $_{(Scarf)}$ *= 141/(141+4+3) =0.9527*

Recall / Sensitivity / TPR $_{(Normal)}$ *= (691/700) =0.9871 Recall / Sensitivity / TPR* $_{(Sunglass)}$ *= (148/155) =0.9548 Recall / Sensitivity / TPR* $_{(Scarf)}$ *= (141/145) =0.9724 Specificity / TNR* $_{(Normal)}$ *=293/(293+4+3) = 0.9766 Specificity / TNR* $_{(Sunglass)}$ *=839/(839+5+1) =0.9928 Specificity / TNR* $_{(Scarf)}$ *=848/(848+4+3) =0.9918 Misclassification Rate* $_{(Normal)}$ *= (9/700) = 0.0128 Misclassification Rate* $_{(Sunglass)}$ *= (7/155) = 0.0451 Misclassification Rate* $_{(Scarf)}$ *= (4/145) = 0.0275 Overall Accuracy = ((691+148+141)/1000) = 0.9800*

Figure 12 depicts the comparison between the true positive rate, specificity and misclassification rate for the proposed approach when tested with real time images. It can be observed that the specificity and sensitivity is very high and that the misclassification rate is minimal is a clear indicator that the classifier is highly accurate with the classification results obtained. Figure 13 shows the graphical comparison of precision and misclassification rate values for AR Face database.

Fig. 8. Some samples taken from AR Face Database

Table- II: Accuracy Percentage for different Image Classes

Image Type	Actual Images	Correctly Classified	Accuracy %
Normal	700	691	98.71
Sun Glasses	155	148	95.48
Scarfed	145	141	97.24

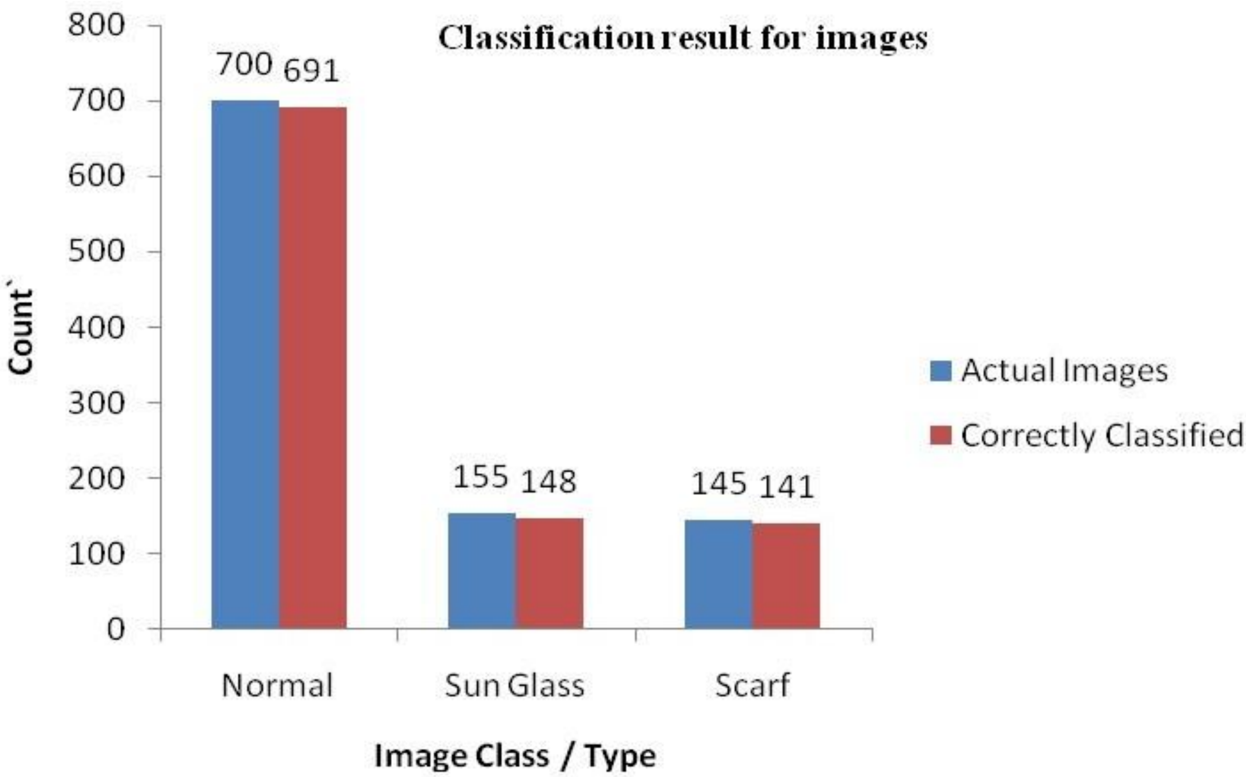

Fig. 9. Classification results for different class of images

Table- III: Accuracy Percentage for different Image Classes Using AR Database

Image Type	Actual Images	Correctly Classified	Accuracy %
Normal	480	469	97.70
Sun Glasses	105	102	97.14
Scarfed	115	112	97.39

Table- IV: Confusion Matrix For AR Face Database

Class	Normal	Sun Glass	Scarf	Total
Normal	469	7	4	480
Sun Glass	1	102	2	105
Scarf	1	2	112	115
Total	471	111	118	700

Table- V: Confusion Matrix For Real Time Dataset

Class	Normal	Sun Glass	Scarf	Total
Normal	691	5	4	700
Sun Glass	4	148	3	155
Scarf	3	1	141	145
Total	698	154	148	1000

Table- VI: Performance Metrics of Proposed Approach for AR Face Dataset

Parameter Normal	Sunglass	Scarf	
True Positive	469	102	112
True Negative	218	586	579
False Positive	2	9	6
False Negative	11	3	3
Precision	0.9957	0.9189	0.9491
Recall / Sensitivity/ TPR	0.977	0.971	0.974
Specificity / TNR	0.9909	0.9848	0.9897
Misclassification Rate	0.023	0.028	0.026
Accuracy	0.9757		

Table- VII: Performance Metrics of proposed approach for real time Image set

Parameter Normal	Sunglass	Scarf	
True Positive	691	148	141
True Negative	293	839	848
False Positive	7	6	7
False Negative	9	7	4
Precision	0.9899	0.9610	0.9527
Recall / Sensitivity/ TPR	0.9871	0.9548	0.9724
Specificity / TNR	0.9766	0.9928	0.9918
Misclassification Rate	0.0128	0.0451	0.0275
Accuracy	0.98		

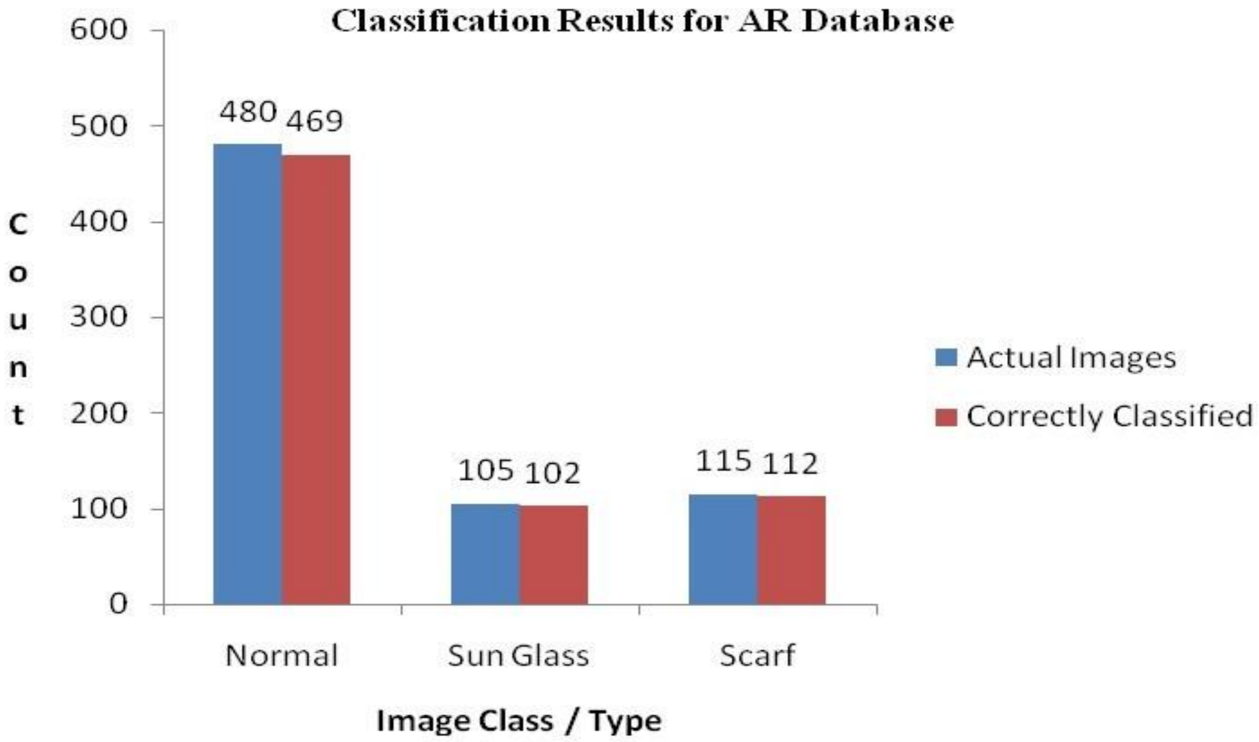

Fig. 10. Classification results for AR Database

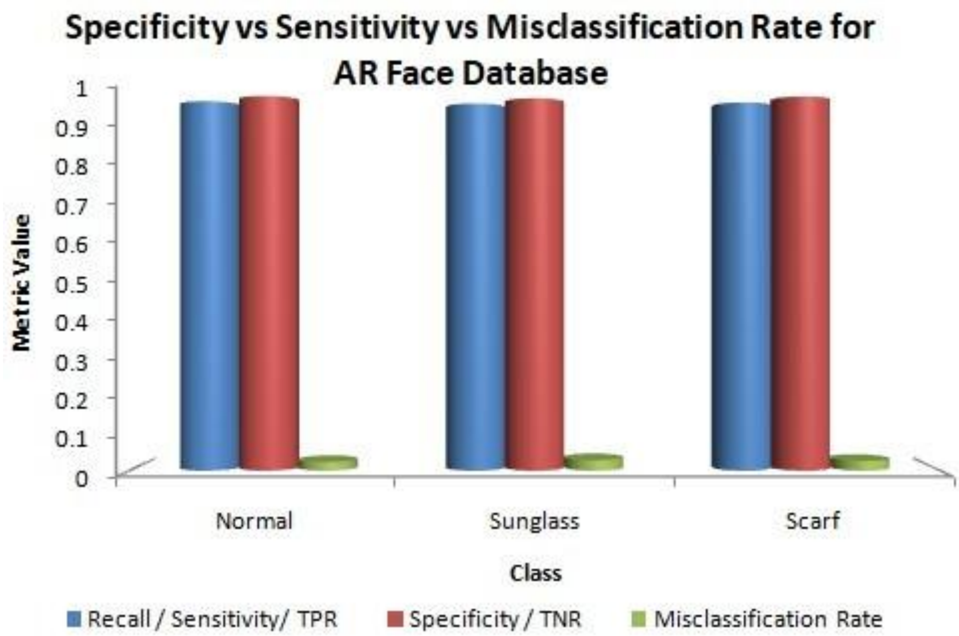

Fig. 11. Specificity vs Sensitivity vs Misclassification Rate for AR Face Database

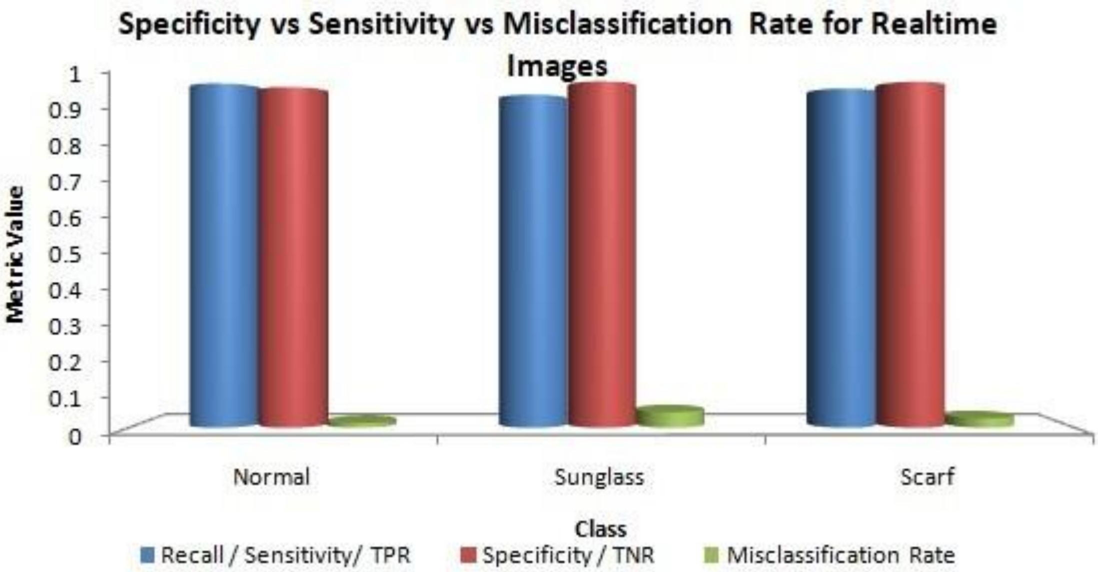

Fig. 12. Specificity vs Sensitivity vs Misclassification Rate for Real time image set

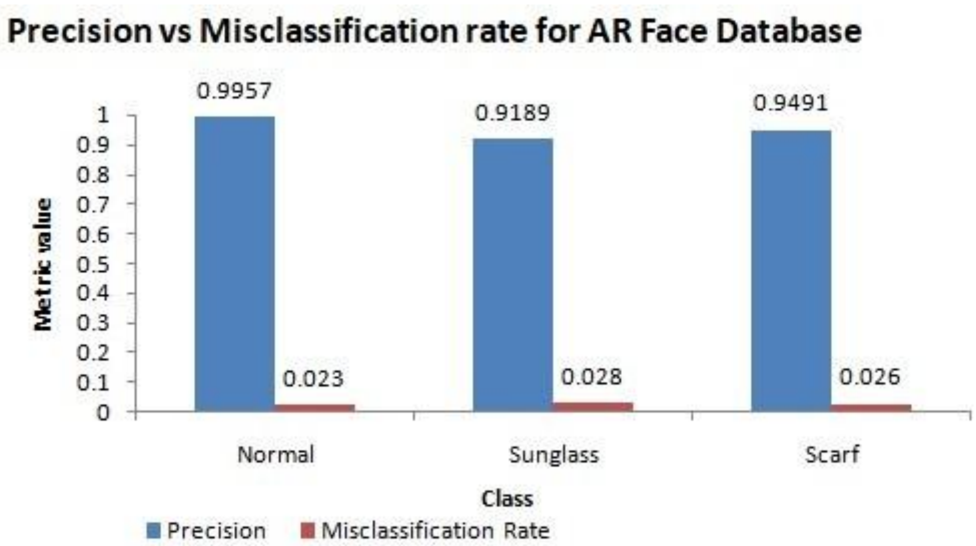

Fig. 13. Precision vs Misclassification Rate for AR Face Database

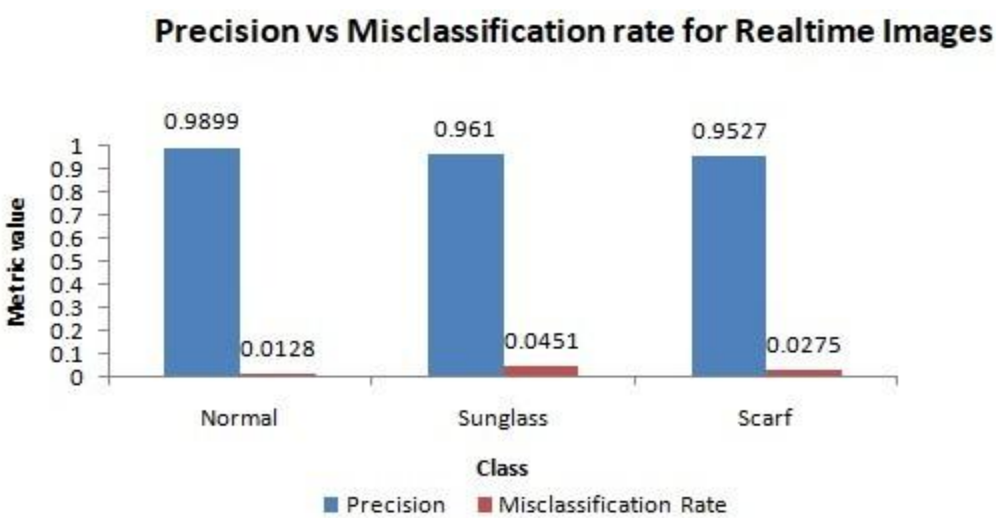

Fig. 14. Precision vs Misclassification Rate for Real time images

Figure 14 corresponds to the graphical comparison of precision and misclassification rate values for the real time image set. The higher values for precision, recall, specificity and sensitivity and very minimal values of misclassification rate for the three different classes namely normal, sun glass and scarf means that the result of the classifier is very accurate and robust.

B. Challenges Faced

The proposed system was tested with both images captured in real time and AR face database. Few difficulties were experienced when the illumination was very poor such as dark rooms, closed area where no lighting was available. This resulted in some misclassifications and reduced the accuracy of the proposed approach.

VII. CONCLUSION AND FUTURE WORK

As part of this work, a new approach to detect partially occluded faces has been proposed. Results indicate that the accuracy percentage for real time images as well as results derived out of testing with AR Face database showed accuracy percentage higher than 97% with greater values of precision, sensitivity and specificity along with minimal misclassification rate for both AR Face database and real time images.

This work can be extended into developing a sophisticated smart camera which can identify occluded or masked faces and also serve as an efficient security system which can be deployed across banks, ATMs, party halls etc to detect suspicious faces which are partially occluded.

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