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Gender Classification from Facial Images

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Abstract : Gender is one striking feature that human can deduce effortlessly when looking at a face. Here, we try to classify the gender (male or female) based on the face images. The first part of this paper presents a review of different methods/approaches used for gender recognition. We present a comparative analysis for gender recognition using PCA, 2dPCA and its variants. Finally, we develop an iterative model using 2dPCA which updates itself when new samples are encountered. This model is expected to be fruitful in real-life situation as it can learn when it comes across new test samples. We consider CFD, CUHK, ORL and Yale facial data-sets for our experiments.

Keywords : Gender Recognition, PCA, 2dPCA.

I. INTRODUCTION

Humans are very accurate and fast in visual categorization using face visuals. Among the different categorization, gender is the one of them, by which humans can identify people. Before 90's, gender recognition was one of the most studied topic in psychology.

In 1995, Harve Abdi et. al. [1] performed a simulation for evaluating codes based on pixel for gender recognition. This simulation work paved the way for a new direction, i.e. gender classification, in the field of computer vision using face image. RBF(Radial Basis Function) was one of the two classifiers. Perceptron was the 2nd classifier they used in their simulation. Their representation of faces is known as eigenvectors (also known as principal components). They modelled four networks for gender classifications and they were[1]:

- ✓ An autoassociator followed by RBF network that operate on the projections of the faces onto the eigenvectors of the memory matrix.
- ✓ An autoassociator followed by a perceptron that operate on the projections of the faces onto the eigenvectors of the memory matrix.
- ✓ A RBF network trained directly on the pixel representation of the faces.
- ✓ A perceptron trained directly on the pixel representation of the faces.

The dataset contained 160 facial images and out of which 159 images were used to train the network iteratively. Each time 1 image was left out purposefully for testing.

J. Yang and others [2], in their paper developed a appearance-based method, known as 2dPCA (Two Dimensional PCA). Unlike PCA, in 2dPCA the image matrix remains the same, i.e. 2D, before the feature extraction process. They performed different experiments for the testing of the 2dPCA method. They also evaluated its performance. While testing and evaluating 2dPCA, the face image datasets, they considered, are: Yale, ORL and AR. Their experiments were related to recognition. The experiments showed that 2DPCA gives better rate of recognition than PCA for all of the three datasets.

M.C. Santana and Q.C. Vuong [3] presented an analysis of the diagnostic areas and the solutions could be adopted for classifying the gender. First, they made a database of 7000 images, collected from the internet randomly. Around 3400 images were considered for the training and the remaining images were considered for testing purposes. Then computation of a no. of classifiers based on SVM(Support Vector Method) were performed. Based on this, 100 eigenvalues are employed for the representation of face. Again, they used a video stream database (1130 streams) from the television broadcast. The total no. of subjects contained in the video stream databases was 850. PCA [4] approach was employed for the face representation. At the beginning the training set was empty. Each time the system met an individual (randomly), it classified the individual. After classifying all of the individuals, not necessarily with 100% accuracy, the incorrectly classified individuals were again fed into the system for updating the classifier for gender recognition. After analysis, they found that humans not only consider the inner face regions but also the outer face regions also. They also concluded that 18X22 is minimal resolution for the classification of gender correctly.

Taskeed Jabid et. al [5], in their paper, presented a texture descriptor called LDP(Local Directional Pattern) for face image representation to classify the gender. Here, each of the pixels of an image was assigned with a binary code of 8-bits. For the calculation of the pattern, they compared the relative edge value of a pixel along the eight pre-determined directions using Kirsch Masks. High response value in a particular direction means the presence of corner/edge in that direction. For their experiment they used the FERET face database. For representing face, using LDP, the steps they followed are:

(i) Generation of LDP face image,
(ii) Generation of LDP Histogram.
(iii) Division of the face image in to 'n' regions.
(iv) Generation of LDP histogram for each of the 'n' regions.

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(v) Concatenation of n LDP histograms for a combined LDP histogram for the representation of global face feature for that image.

The face feature thus generated was used for classification of gender using SVM. With an accuracy of 95.05% they proved that the performance of the proposed LDP+SVM is better than LBP+Chi-square and LBP+Adaboost.

HU Jian-jun and others [6] presented a study comparing the two important methods PCA and 2dPCA, which involved dimensionality reduction, for face recognition. They proposed a new concept known as CID (Column-Image Difference) and consisted of two parts: SCID (Same Column-Image Difference), DCID (Different Column-Image Difference). They presented the relationships of both the PCA and 2dPCA with CID. They also presented a detailed performance analysis of PCA and 2dPCA based on CID considering four conditions, as described in Table-I.

Table-I: Performance Analysis of PCA & 2dPCA with four conditions

Condition	Facial Expression	Posture	Illumination	Better Method
1	changed a little bit/ unchanged	changed a little bit/ unchanged	unchanged	PCA
2	changed greatly	changed greatly	unchanged	2dPCA
3	changed a little bit/ unchanged	changed a little bit/ unchanged	changed	Same but PCA is more robust
4	changed	changed	changed	2dPCA

For their study they considered four face image databases namely- Yale, Yale B, AR (consisted of 3 groups of images) and UMIST. They performed three experiments considering the above conditions (in Table-I) using the above mentioned databases. The 1st experiment showed the superiority of 2dPCA over PCA, where 1st group of AR and UMNIST databases we considered. But the 2nd experiment, where 2nd group of AR and Yale B were used, showed that PCA is far superior to 2dPCA. The 3rd experiment, which used Yale and group-3 of AR databases, showed that (i) with Yale 2dPCA is better than PCA but (ii) with group-3 of AR PCA outperformed 2dPCA. With the above results they concluded that there was no concrete and convincing evidence to say 2dPCA always outperform PCA.

D. Deshmukh [7] presented an experiment for gender recognition using SVM. For his experiment he created his own face database. For the facial feature extraction, he followed the steps:

(i) Definition of facial features i.e. for face, left and right eye, mouth and nose,

(ii) Alignment of face if the face in a image was inclined to horizon.

(iii) Extraction of facial features in the database.

He did a performance analysis by comparing the error rates for SVM, Nearest Neighbour and Fisher Algorithm and result is shown in Fig.1.

A. Ignat and M. Coman [8] performed feature extraction using Gabor Filters to get the information significant for gender with various orientation angles. They also tested state-of-the art classifiers on the AR and FERET face databases. In their experiment, their methodology was-

(i) Extraction of the features using Gabor filters,

(ii) Classification of gender using- SVM, k-NN, Linear Discriminant Analysis (LDA) and Neural Networks.

Finally, they compared the performances of the above classifier methods (Table II).

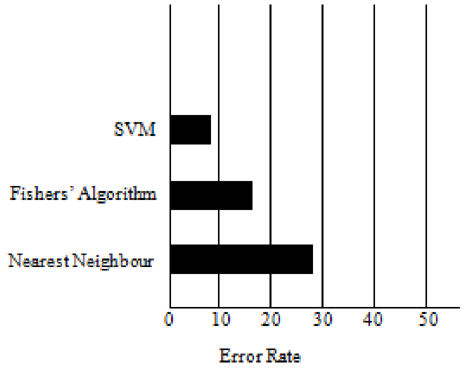

Fig. 1. Comparison of error rate [7]

From the experiments and performance comparison they concluded that the use of Gabor filters in feature extraction could also produce good features which in turn could give classification results comparable with the other feature extraction methods studied.

Table-II: Average Classification Rates (%)

Database	SVM Linear	SVM RBF	LDA	Neural Network
FERET + AR	97.34	95.91	95.53	96.2

A. Dantcheva and F. Bremond, in their paper [9], proposed a method for estimation of gender. In their research, they mainly focused on “Smile”, a common facial expression. They also studied about the smile could also be considered as one of the evidence for gender classification. Using Viola-Jones algorithm they detected the face from the input facial image. After detection, they used a detector, proposed by Asthana et al. [10], for detection of facial landmarks- eye-brow, eye and mouth regions (shown in Fig-2).

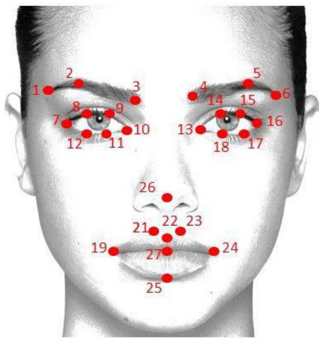

Fig. 2. Detected Landmarks in a face [9]

They then extracted the dynamic-features and selected 27 facial distances, based on facial movements during smile expressions, e.g. widths of right and left eyes, lengths of left and right eyes, and distances between eye-brows and so on. Thus they got 24 features.

For gender classification they used SVM, AdaBoost and Bagged Trees. For the experiments, UvA-NEMO Smile dataset was used. There were multiple video sequences of 400 individuals and out of which 185 were females and 215 were males. The age of the individuals varies from 8 to 76. For the performance evaluation of their proposed algorithm, they divided the dataset in to 15 folds (each containing approximately 24 individuals. From their experiments, they observed that dynamics outperformed the appearance based features for the individuals whose ages were less than 20. But for older individuals, appearance based features were more dominant than dynamic-features. Finally they analyzed the gender-dimorphism of both, spontaneous and posed smiles and observe that both carry substantial cues for gender [9].

II. PCA AND 2DPCA

A. PCA

PCA[6], also known as Karhunen-Loeve Transform, is a widely used dimension reduction tool which tries to derive the projections that maximises the scatter and also with minimum reconstruction error. PCA operates in the vector-space where a 2d image is reshaped to a 1d vector by row/column concatenation. If x_i is a m*n image then it is transformed to a vector of dimension (mn) which tends to be very large. Let D be a set of N images of dimension (m*n). PCA maximizes the scatter, S defined as

$$S = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T.$$

If W is the transformation matrix, then the optimal value of W will be the one that maximises the trace(S), that is $W_{opt} = \arg\max_W |W^T S W|$ which corresponds to the eigenvector of S paired with the largest eigenvalue of S. Generally, one eigenvector is not sufficient as most of the information would then be discarded, so a set of k eigenvectors are selected corresponding to the k largest eigen values of S.

$$Y = W^T * D \qquad \text{.................(1)}$$

gives the projections of the original images in the new space where $[W]_{(mn*k)}$ and $[D]_{(mn*M)}$ are the transformation and data matrix respectively. Note that Y is of dimension k*M where k<<M and therefore the dimensions of the images are greatly reduced from mn to k.

B. 2dPCA

In contrast in PCA, 2dPCA[6,11] uses the images in its 2-dimensional form to develop the scatter matrix as opposed to the standard PCA which reshapes the images to a 1-dimensional vector. The scatter matrix obtained in 2dPCA is much smaller than that of PCA which results in major computational efficiency in the former. Also, the spatial information, which was lost in vectorizing the image in PCA, can be put to use through 2dPCA.

Unlike in PCA, the image scatter matrix in 2dPCA, G_t, is defined as

$$G_t = E[(A - E(A))^T(A - E(A))]$$

$$= 1/M \sum_{i=1}^{M} (A_i - \mu)^T (A_i - \mu) \qquad \text{................. (2)}$$

Here, A is an (m*n) image, μ is the mean image and M is the total number of images.

If X is an (n*1) transformation vector, then the optimal projection X_{opt}, will be the one that maximises the total scatter of the projected images. X_{opt} is then given by the general eigen value solution of

$$X_{opt} = \arg\max_X |X^T G_t X| \qquad \text{.................(3)}$$

which corresponds to the eigen vector having dimension (n*1) of the largest eigen value of G_t. Thus, Z_i, the projection of the i^{th} image, A_i is given by

$$Z_i = A_i * X_{opt}$$

Note that the 2dPCA projection of the (m*n) image, Z_i, is a (m*1) vector, unlike a scalar as in PCA. If d eigen vectors are selected then the projection of the image would be (m*d) where d<<n, which is also 2-dimensional.

The equation in (3) is actually a derivation of the objective of 2dPCA which is to maximise the total scatter of the projected images which can be measured by the trace(S), where S is the covariance matrix of the projected images (Z_i) given by:

$$S = E[(Z - E(Z))(Z - E(Z))^T]$$

$$= E[(AX - E(AX))(AX - E(AX))^T]$$

$$= E[[(A - E(A))X][(A - E(A))X]^T]$$

Now, the trace of S is given by:

$$tr(S) = tr(E[[(A - E(A))X][(A - E(A))X]^T])$$

$$= X^T[(A - E(A))^T(A - E(A))]X$$

$$= X^T G_t X$$

and thus (3) follows.

Owing to the 2-dimensional features of 2dPCA, the method for measuring the distances between two projected images differs from the ones where the features are one dimensional. As Yang et al., the founder of this technique has proposed, the distance between two 2d features of two images, is computed as the total distance between the individual column vectors of the output features i.e.,

$$dist(I_m, I_n) = \sum_{i=1}^{k} \left\| Z_i^{(m)} - Z_i^{(n)} \right\|_2 \qquad \text{................(4)}$$

where $Z_i^{(m)}$ and $Z_i^{(n)}$ are the i^{th} columns of the projected images I_m and I_n. For a test sample, t, it is assigned the class of the nearest neighbour.

2dPCA is actually the PCA of the rows of a matrix, where the rows are taken as a computational unit. This is the advantages of 2dPCA over PCA. As the dimension of the row vectors is much smaller than the dimension of the entire image when reshaped into a 1D vector, the curse of dimensionality problem does not arise here. Also, as the computational units, which are all the rows of the sample images, are much larger than the number of available images, the Small Sample Size (SSS) problem also vanishes. The SSS problem occurs when there are lesser number of samples(t) than the dimensions(d) which makes the rank of the covariance matrix to be (t-1) or less which is way less than d, making the covariance matrix singular. Also, the recognition accuracy of 2dPCA seems to outperform the standard PCA. The Fig. 8 depicts this fact.

III. EXPERIMENTS

Our experiments are related to gender classification and are divided in to two parts:

A. 2dPCA is explored for gender recognition on the CFD dataset. Also, its ramifications are studied alongside. Here, we have carried-out experiments applying 2dPCA and a concept 2dPCA with 2D-to-1D conversion. Here, we have used the full-face and half-face of the subjects.

A.1 Data Set

For our experiments, we have considered the Chicago Face Database (CFD)[11]. This dataset holds image samples belonging to different ethnicities such as Mongoloid, Black, Latino and White with a total of 526 male samples and 596 female samples. The images have a high resolution of 2444*1718. The images are all frontals with different expressions ranging from neutral, anger, happy (with and without teeth displayed) and surprised. Some of the samples from the dataset are shown in Fig. 3. Our training set consists of 70% of the total samples with equal nos. of positive (male) and negative(female) samples. And the rest 30% constitutes our test set.

Fig.. 3. Original samples of one subject with varying expressions

A.2 Pre-processing

The following procedure is followed for pre-processing, so that the images constitute of face information and minimal non-face data.

1) The image is converted from RGB to grayscale and the face region is extracted using [12].
2) 68 facial landmarks [13] are detected using the method, implemented in the DLIB module.
3) The face is then aligned such that the eyes appear 35% inwards from both its side edges and center of the mouth appears 20% from lower edge of the image.
4) The image is resized to a size of (40*40).

Few of the pre-processed images are shown in Fig. 4. Most of the background is eliminated so that the images constitute of face information.

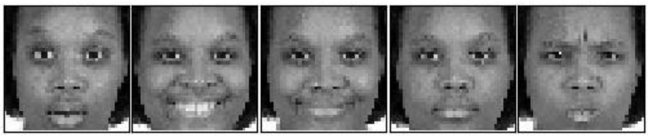

Fig. 4. Aligned images of the subject with various expression

A.3 Experiment-1

In this experiment, we use:

a) 2dPCA for feature extraction,
b) Nearest Neighbor, based on the equation-4, for gender classification.

A.4 Experiment-2

Though 2dPCA is advantageous in feature extraction than the standard PCA, it has a downside with respect to the time taken for the classification task as for a (m*k) projection matrix, '*k*' L2-norm(s) (Euclidean distance(s)) corresponding to the k column vectors have to be calculated and summed over to compute the distance between a test and a train image. To enhance the time efficiency, we revert the 2d-features to 1d by flattening (concatenating the rows one after another) the 2d matrix and compute the distances between the test and train images.

In this experiment, we use:

a) 2dPCA, with 2D to 1D transformation, for feature extraction,
b) Nearest Neighbour(k-NN) Classification technique for gender classification.

A.5 Experiment-3

As the face is longitudinally symmetrical, one half of the face is used to explore its competency in gender recognition and was introduced by N. Ramanathan and others[14]. M.P Satone and G.K. Kharate [15] used the half-face approach in face recognition. To the best of our knowledge, we will use this approach to explore gender classification for the first time. This approach reduces the computational cost as lesser information is required to encode a half face. Using the half face would also make the model perform even when the test image is subjected to partial occlusion. In our experiment, the half face images are of sizes (40*20) making a total of 800(40*20) pixels in contrast to 1600(40*40) pixels in full face. The covariance matrix size is also reduced to (40*20). The half face region is extracted from an input RGB face images using the following procedure-

1) The face region is detected using the popular Viola-Jones algorithm.[12]
2) Facial landmarks are detected as in section III-A.2. Using the landmark coordinates, extract the region corresponding to the right edge of the face to the middle of the nose and from the forehead to the chin of the face.
3) Resize the subarray to the size (40,20).

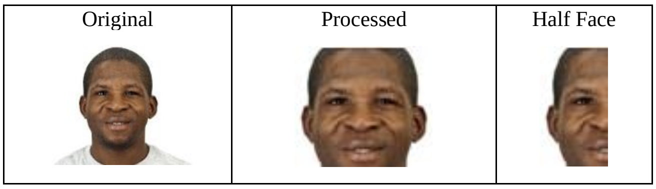

Fig. 5: Original, Processed, Half-face of the subject

Now, we divide our experiment in to two sub-experiments:

Experiment-3.1: as described in experiment-1 but with the half face instead of full face.

Experiment-3.2: as described in experiment-2 but with the half face instead of full face.

B. Boosted Iterative Model

It is generally seen that a model is designed and tested on a particular dataset or with an amalgamation of more than one dataset where the test data shares the same environment with the train data. But when unseen data is provided for testing, the model tends to degrade. This is undefying in nature as the new test samples may vary in many different aspects like illumination, pose, expressions and so on. To counter this, we have come up with an iterative model which upgrades itself upon failing with new test samples. This model is motivated from [3] which also uses an incremental approach. Our model differs from [3] in the following ways:

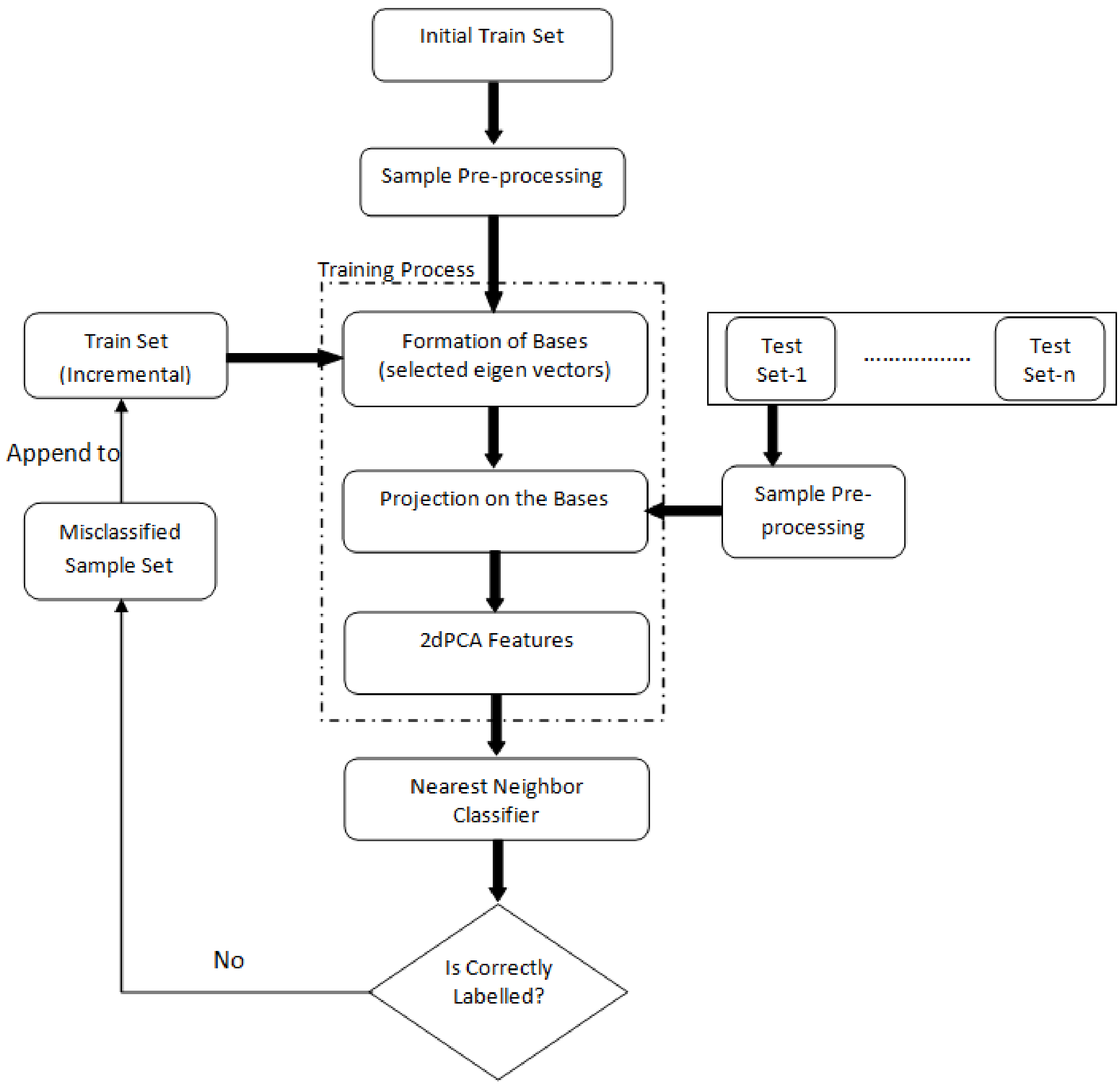

Fig. 6. Flow Diagram for the Boosted Iterative Model

- Test datasets are manually partitioned in such a way that unseen subjects are encountered every iteration, the images of which are neither included in the previous test set nor the train set.
- Four databases namely ORL, Yale, MR2, CUHK are assembled, each of which differ in their visual environments like illumination and posture as well as the subject's ethnicity.
- 2dPCA, instead of PCA, features are used.

The steps followed in this model are:

Step -1: $Train_0$ = 526 images, which is about 50%, of the CFD dataset are used as the initial training set.

Step -2: For $i = 1,2,\ldots\ldots,n$

Step -3: Eigen vectors of the Covariance matrix are derived and 10 eigen vectors are selected as the new bases.

Step -4: $Test_i$ = ith set from the pool of test sets.

Step -5: Train and test samples are projected onto the new bases to output the 2dPCA features.

Step -6: Nearest Neighbour classification of the test samples is done according to [2].

Step -7: Find misclassified samples, m_i

Step -8: $Train_i = Train_{(i-1)} + m_i$

Step -9: Go to Step -3.

For this approach, we make use of the data from CFD, ORL, Yale, MR2, CUHK and Internet source. We split the CFD dataset into three subsets in the ratio of 5: 2.5: 2.5. The first part which consists of 50% of the CFD data is used as the initial train set. The other subsets of the CFD set each of which comprises of 25% of the dataset are used as test sets in the first and second iterations. ORL, MR2, YALE and CUHK datasets are combined and divided into several parts and each of them are used as test sets in the subsequent iterations. It is to be noted that every 'part' holds images of different subjects and no part shares images of the same subject; this makes the 'parts' disjoint.

Before training or testing, the images undergo pre-processing as described in section III-A.2.

In every iteration, the accuracy is assessed and the misclassified samples are appended to the train set. As the train set grows (in size) with every iteration, new features (2dPCA) are extracted and are used for testing the new test set. Though ORL, Yale and the other datasets are employed here those differs from CFD in terms of illumination, scale, expression and pose, this approach exhibits improved performance with every growing iteration. Lastly, images collected from internet are used for testing. These images are largely diverse in nature than those which the model is trained on.

IV. EXPERIMENTAL RESULTS

- **Analysis of Experiments conducted in section III-A**

The graph in Fig. 8 shows the time taken for the classification task performed as in experiment-1 and in experiment-2. A clear difference is noted for both the cases. Though in both the experiments, classification is done with Nearest Neighbor, it is seen that vectorized image takes lesser time than its 2-dimensional counterpart. This is due to the difference in the method of calculating the distance between two images. As discussed in section III-A.4, for (m*k) projection images, 'k' L2-norms have to be calculated; while for vectorized images only one distance is computed thereby reducing the square root operations from k to1. Therefore, flattening the 2dPCA outputs is advantageous in terms of computational time.

In experiment-3, since the half faces need relatively lesser number of pixels than a full face, the overall computational cost is bound is going down. As already mentioned, that in the experiment the covariance matrix is also reduced to a certain size, the eigen vector decomposition and the projection time of the train and test samples are relatively reduced than the full-face counterpart.

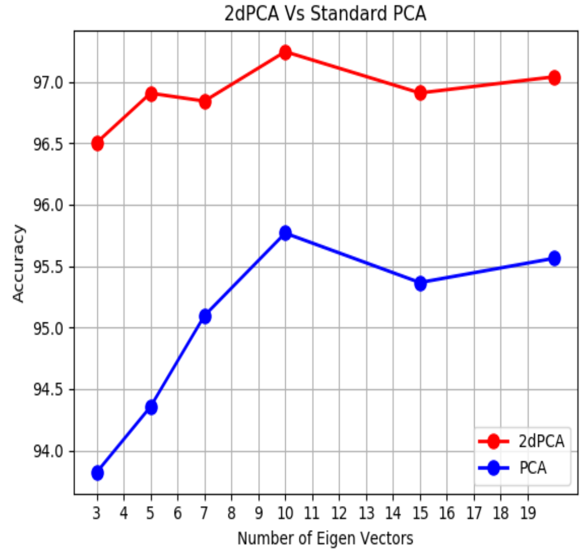

Fig. 7. Gender Recognition Accuracy: 2dPCA vs. PCA

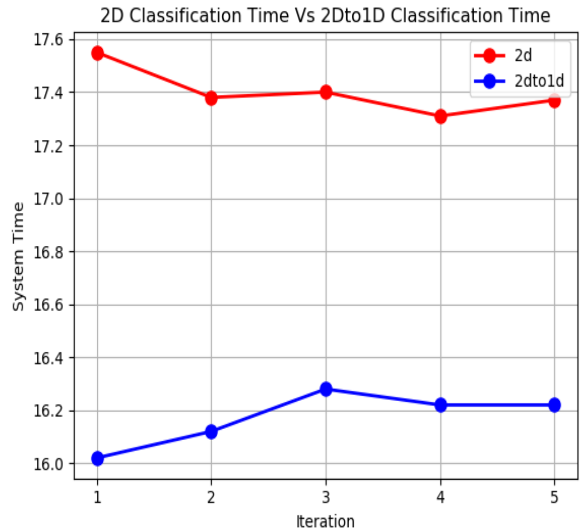

Fig. 8. Classification Time: 2D vs 2D-to-1D

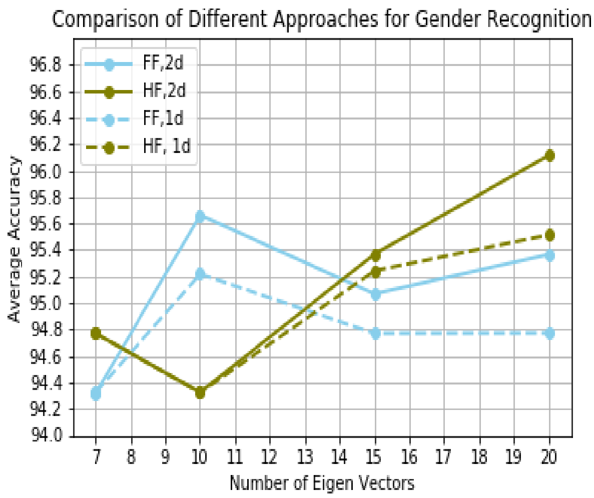

Fig. 9. Gender Recognition: Full-Face vs. Half-Face

Fig. 9 shows the graph of the average accuracy of gender classification obtained after five iterations for full face and half face images which combines the experiment-1, experiment-2, experiment-3.1 and experiment-3.2. It is clearly seen from the graph that the half face is also equally competent as full face for determining gender. At the same time, from the graph , we see that:

i) the average accuracy for the full face 2dPCA approach is better than the full face 2D-to-1D 2dPCA approach and,

ii) the average accuracy for the half face 2dPCA approach better than the half face 2D-to-1D 2dPCA approach .

But as discussed above (Fig. 8), the classification time for 2dPCA is more than 2D-to-1D 2dPCA.

So, from the results and discussions, it would be worth to say that half-face posesses discriminative information for gender classification.

Also there is a trade-off between classification time and classification accuracy in terms of the usage of 2dPCA and 2D-to-1D 2dPCA. But keeping the progress of technology in mind we can sacrifice classification time for better classification accuracy.

- **Result Analysis of the Boosted Iterative Model (in section III-B)**

Table-III shows the performance the model.

Table-III: Analysis of Boosted Iterative Model

Iteration	Train Set	Test Set	Misclassified Set	Accuracy (%)
1	T1 [CFD(50%]	CFD1 (25%)	M1(6%)	94
2	T2=T1+M1	CFD2 (25%)	M2(4.8%)	95.2
3	T3=T2+M2	*C1	M3(32%)	68
4	T4=T3+M3	*C2	M4(25.9%)	74.1
5	T5=T4+M4	*C3	M5(23.1%)	76.9
6	T6=T5+M5	Internet	M6(26.7%)	73.3

* C1, C2, C3 = 30% of [CUHK+MR2+Yale+ORL] each

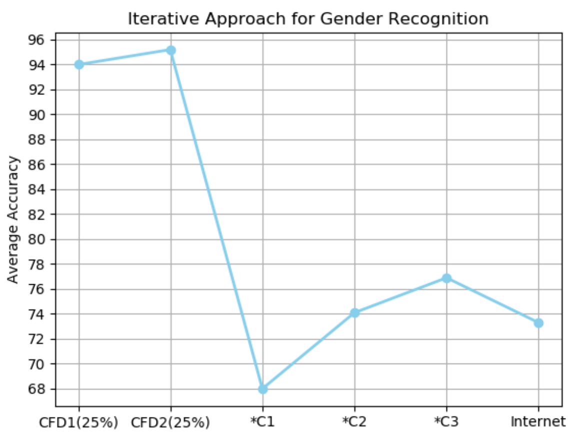

Fig. 10. Performance of the Boosted Iterative Model

As shown in fig. 10, a sharp descent is noticed when test samples of a new data-set (CUHK+MR2+Yale+ORL) are used for very first time. This is expected as there are differences in the environment of the testing set with original train set. But as the number of iteration increases, a steady rise in performance is noticed. Finally, model is evaluated with images collected from the Internet and a it is able to achieve nearly 74% of classification accuracy. It indicates that our model tends to get better with new facial image exposures.

V. CONCLUSION

From the first experiment it is seen that 2dPCA shows better performance than PCA with the CFD dataset where facial expressions varies greatly. Also, when the 2D outputs are vectorised (in 2D-to-1D transformation in experiment-2) time is gained with the price of slight accuracy drop. Experiment-3 shows that half-face proves to be a competent candidate for gender classification. In the iterative model presented here, the training set size grows with time which can be tackled with incremental learning approach.

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