Gabor Filter Based Face Recognition Using *Non-frontal* Face Images

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ABSTRACT

Face recognition has immense real world applications in the field of computer vision and a challenging task especially when the frontal face images are not available to train the classifiers. In this paper by regulating the scale and orientation parameters of Gabor Filters, we obtain high dimensional features from the face images with different poses. To classify the images, first we partition the images using k-means clustering algorithm where k varies from 6 to 8 for different databases representing pose variations of input images. Based on the clustering we assign class labels to the training data set for recognizing non-frontal face images with variant poses. To reduce the complexity of the system, different statistical properties of the features like variance, entropy, and correlation coefficient are analysed to select significant features only. Removal of irrelevant features, effectively reduces dimensionality of the feature space without sacrificing accuracy which is 94.47%. The proposed approach performs better compare to the existing methods, with and without feature selection algorithm.

Keywords

Gabor Wavelet, Feature Selection, Variance, Correlation Coefficient, Entropy

1. INTRODUCTION

Acquisition of frontal face images are not always possible and so the problem of face recognition from non-frontal face images attract researchers in the field of Computer Vision. Few face recognition algorithms have been proposed till date to recognize the non-frontal face images. Non frontal faces can have different head poses which are caused by the displacement of faces in pan(Left and right) and tilt(top and down) direction. Therefore, face recognition using pose variant training images require input features which can capture different orientation of the faces.

Gabor filtering is a popular approach to extract features from the face images with different orientations by convolving the image with the Gabor wavelet basis function. Every image produces a large number of Gabor filtered images depending upon the number of scale and orientation. Famous algorithm named ***"Elastic Bunch Graph Matching"*** (EBGM) [21] [1] uses Gabor filtering in its basic step. A set of landmark locations on the test face are chosen and labeled with the Gabor filter responses, applied to a window around the landmarks. These magnitude responses are represented by Gabor jets and collected in a data structure called bunch graph. Graphs for new face images can then be generated automatically by Elastic Bunch Graph Matching algorithm. Recognition of a new face image is performed by comparing respective image graph to those of the known face images and identifying the one with highest similarity value. It is to be noted that the methods described in [13][21][1], are partially robust to changing facial expressions and illumination variations, however, do not perform well for face recognition using non-frontal face images. A modified EBGM algorithm [3] has been proposed to recognize non-frontal faces, however the method has dependency on image database under consideration. Features obtained using Gabor filter responses are large in dimensionality due to capturing scale and orientation information, essential for non-frontal face recognition.

The down- sampling techniques reduce the dimensionality of the Gabor magnitude responses by retaining only the values located at the intersection points of different grids, while discarding the rest. The down-sampling procedure is applied to all magnitude responses, which are ultimately normalized using appropriate procedure and then concatenated into the final Gabor (magnitude) face representation [13]. There are various dimension reduction algorithm in use, but, they too have shortcomings. ***Linear Methods*** like PCA [18] is used for dimensionality reduction by selecting only few principal components resulting loss of information. MDS(Multi Dimensional Scaling) [20] is based on the pair wise distance of two data points and therefore, linear. LDA (Latent Dirichlet Allocation)[18] [6] is a linear mapping and works well only on data which is close to Gaussian distribution. In Indepensent Component Analysis (ICA) [11] each vector is represented by a linear combination of some independent latent component. ***Non-linear Methods*** for dimension reduction like,

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ISOMAP [20] preserves the geodesic distance between two data points instead of the Eucledian distance. So, it keeps the non-linearity during functioning, but it does not work well on new sets of data points. Same is the problem with Locally Linear Embedding(LLE) [14]. Kernel PCA (KPCA) [15] [20] first projects the data onto another space, of greater dimension by using a kernel matrix and then performs with conventional PCA. The problem here is choosing the right kernel and also the size of the kernel.

The objective of the paper is to recognize a person accurately with different poses by extracting important features from non-frontal face images. By investigating different pose variant images, and applying K-Means clustering algorithm we first assign class labels to the training data set representing different poses of the persons. A face recognition technique based on Gabor filter response of non-frontal face images is proposed in this paper to capture different orientations of the face images and tested on ***Database1*** and ***Database2***. ***Database1*** contains 10 different head pose orientation images of 38 randomly chosen individuals of PIE Database[17] [16] and ***Database2*** contains 15 different head pose orientation images of 15 randomly chosen individuals of Head Pose Image Database[8]. The response of the Gabor filter on each image generates a set of features of dimension $128X128X40$ while considering five scales and eight orientations applied on image size $128X128$. Initially we achieve 94.3% accuracy for face recognition while applying Interpolation method on the total feature set. However, due to large dimensionality of the feature space, computational complexity was often unmanageable.

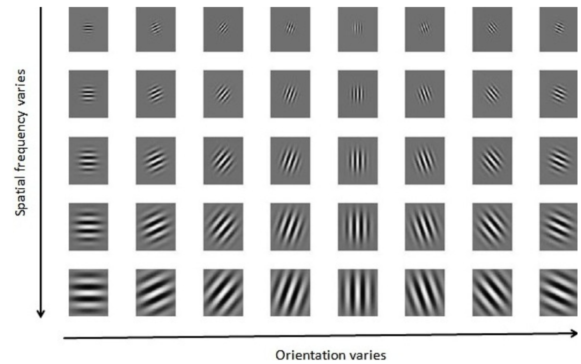
First we have built feature vectors from Gabor Filter responses with dimension $640X40$, containing redundant information. A dimensionality reduction strategy has been proposed in the paper to select features which are important for face recognition. We have analyzed different statistical properties of the features like entropy, variance and correlation coefficient based on which features are selected. The proposed method selects features almost 3/5 th of the original size without compromising classification accuracy.

The paper is organized as follows: Section 2 describes the Gabor filtering procedure used in face recognition. The proposed feature extraction method using Gabor filter has been presented in Section 3, while dimension reduction technique is proposed in Section 4. Results are shown in Section 5 considering different databases and Conclusions are arrived at Section 6.

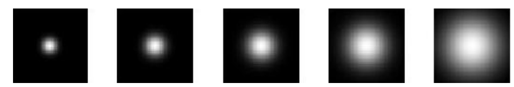
2. GABOR WAVELET

Complex Gabor function was first introduced by Dennis Gabor [7] where he proposed a ***"Quantum Principle"*** for information, similar to ***Heisenberg's Uncertainty Principle*** in Quantum Mechanics. This principle states that an information diagram having coordinates time and frequency, a signal can occupy a certain minimal area, calculated by multiplying bandwidth and duration of that signal. This minimal area can be redistributed in shape but not reduced in area in the information diagram [12]. The general family of signals that satisfy this criterion are ***Gaussian-modulated sinusoids***.

The work of Gabor was extended in 2D form by J.G. Daughman, to represent filters with an optimal localization in 2D spatial and frequency domain [4]. This band limited filter extracts multi-resolutional, spatially local features of a confined frequency band [19], as described in *equation (1).*



(a)



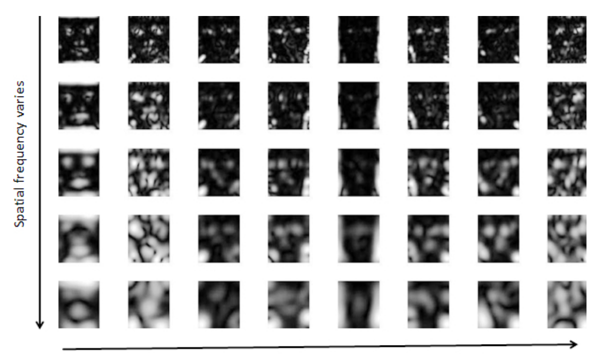
(b)

Figure 1: (a) Real part of the Gabor Filters of the Filter Bank,(b) Magnitude part of the Gabor Filters of the Filter Bank

$$G(x,y) = \frac{1}{2\pi\sigma\beta} e^{-\pi[\frac{(x-x_o)^2}{\sigma^2} + \frac{(y-y_o)^2}{\beta^2}]} e^{i[\zeta_o x + \nu_o y]} \quad (1)$$

where, (x_0,y_0) is the centre of the receptive field in spatial domain, (ζ_0,ν_0) is the optimal spatial frequency of the filter in frequency domain while σ and β are the standard deviations of elliptical Gaussian along X-axis and Y-axis, respectively. In general, the family of 2D Gabor filters can be defined in the spatial domain using *equation (2)* [19].

(a)



(b)

Figure 2: (a) Sample Face Image [10],(b) Gabor Filter Response (Magnitude) images

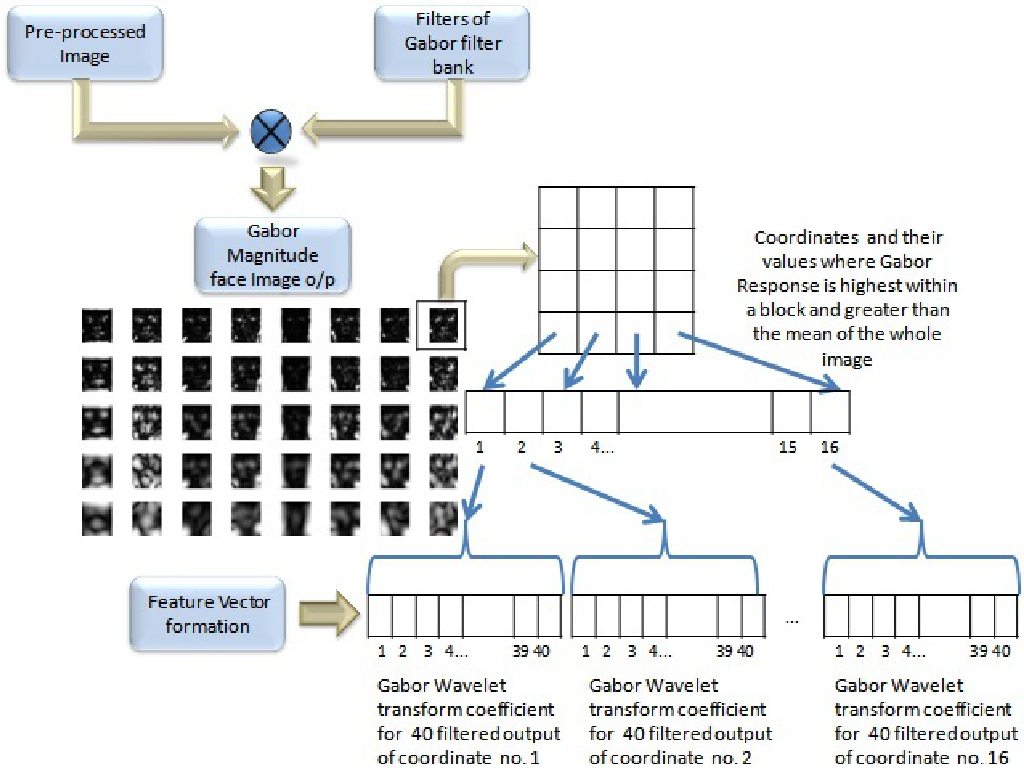


Figure 3: Flow chart for Feature Vector Construction

$$\psi_{u,v}(x,y) = \frac{f_u^2}{\pi\kappa\eta} e^{[(\frac{f_u^2}{\kappa^2})x'^2+(\frac{f_u^2}{\eta^2})y'^2]} e^{j2\pi f_u x'} \tag{2}$$

where,

$$x' = x\cos\theta_v + y\sin\theta_v,$$
$$y' = -x\sin\theta_v + y\cos\theta_v,$$
$$f_u = \frac{f_{max}}{2^{\frac{u}{2}}}$$

and

$$\theta_v = v\frac{\pi}{8}.$$

$\psi_{u,v}(x,y)$ is a Gabor filter representing a Gaussian kernel function modulated by a complex plane wave. f_{max}, f_u and θ_v are maximum frequency, centre frequency and orientation of the filter, respectively whereas the parameters κ and η determine the ratio between the centre frequency and the size of the Gaussian envelope.

2.1 Gabor filter Bank

Different choices of the parameters of Gabor filters determine the shape and characteristics of the filter. The parameters used in the paper are:

$$\kappa = \eta = \sqrt{2} \text{ and } f_{max} = 0.25.$$

The Filter bank featuring filters (each of 128x128 pixels) are of five scales and eight orientations, where *u = 0, 1, . . . , 4* and *v = 0, 1, . . . , 7*. An example of the real part and magnitude of 40 Gabor filters are presented in *figure 1.(a)* and *figure 1.(b)*, respectively. The real parts of the entire filter bank are used in this paper as facial features.

3. FEATURE EXTRACTION

The feature extraction procedure is defined as a convolution operation, as described in *equation (3)* for the given face image I(x, y) with the Gabor filter $\psi_{u,v}(x,y)$ of size u and orientation v.

$$G_{u,v}(x,y) = I(x,y) * \psi_{u,v}(x,y) \tag{3}$$

where $G_{u,v}(x,y)$ denotes the complex filtering output. Here, every image of the face databases are convolved with all the 40 filters of the filter bank, forming 40 filtered outputs each of size 128x128 pixels. The magnitude $A_{u,v}(x,y)$ and phase $\Phi_{u,v}(x,y)$ responses of the filtering operation are computed using *equation (4)*.

$$A_{u,v}(x,y) = \sqrt{Real[G_{u,v}(x,y)]^2 + Imaginary[G_{u,v}(x,y)]^2}$$
$$\Phi_{u,v}(x,y) = arctan(\frac{Imaginary[G_{u,v}(x,y)]}{Real[G_{u,v}(x,y)]}) \tag{4}$$

The magnitude responses of *figure 2.(a)* are shown in *figure 2.(b)*.

3.1 Feature Vector Construction

Convolution of each image of size $128X128$ with Gabor Filters produces a feature space of size $128X128X40$ pixels. To construct the feature vector from this enormous large feature space, we propose an approach as described in *Figure 3*. Every magnitude response image($128X128$) is divided into 16 non-overlapping blocks each of size $32X32$ pixels. Optimum selection of block size ($32X32$) is obtained experimentally, with the justification that a smaller block size produces redundant features and a larger block size produces less number of features resulting information loss. Using ***algorithm 1***, in each block we identify the pixel coordinate (x, y), having highest response and greater than the mean value of the whole magnitude response image. For each magnitude response image, maximum 16 feature vectors are generated and this procedure is repeated for 40 such magnitude responses resulting for each image feature vector of dimension $640X1$. Therefore, the proposed feature vector represents a face in a reduced space and with high information content.

Data: $GABOR\_MAG\{No\_of\_Scale, No\_of\_Orient\}$
Result: $FEATURE\_VECTOR$
$Block\_Size := 32X32, Total\_Filter := 40;$
while $i \leq No\_of\_Scale$ **do**
  while $j \leq No\_of\_Orient$ **do**
    $Current\_Img := GABOR\_MAG\{i, j\}$ **if** $GABOR\_MAG\{i, j\}(x, y) = \max_{(x,y)\in Block} Current\_Img(x, y)$ **then**
      if $Current\_Img(x, y) > \frac{1}{row*col}\sum_{x=1}^{row}\sum_{y=1}^{col} Current\_Img(x, y)$ **then**
        while $Filter\_No \leq Total\_Filter$ **do**
          $VALUE(Filter\_No) := GABOR\_MAG\{i, j\}(x, y);$
        end
      end
    end
    $FEATURE\_VECTOR := VALUE;$
  end
end

Algorithm 1: Algorithm to Extract Feature Vector

4. DIMENSION REDUCTION

The dimension of feature vector for each training image is $640(16X40)$, difficult to handle even if we consider a handful number of images. To reduce complexity, irrelevant and redundant features are removed, effectively reducing dimensionality of the feature space. The dimensionality reduction algorithm is described in ***Algorithm 2***.

4.1 Feature Selection

Entropy is considered as an important parameter for feature selection because it measures average information content in presence of uncertainty. More uncertainty in an image represents more information, measured using *equation (5)*. So, Higher the entropy, more is the information content thus more the importance of the feature.

$$H(X) = \sum_i P(X_i) \log \frac{1}{P(X_i)} \tag{5}$$

where, X is a random variable, representing feature vector and P(X_i) is the probability mass function of X_i. We have arranged the feature vectors of each image in decreasing order according to their entropy.

Another important statistical property of variables is variance and used for feature selection obtaining distinct information in the training data set when the features are more variant to each other. So, for each image we have calculated the variance and the features with variance greater than th_var indicating threshold of feature variance and th_entrp indicating threshold entropy (decided experimentally) are chosen to select important features. Due to large variability in the training images, each image generates a different number of features and minimum of it (say,L) is considered to build equidimensional feature vectors for training.

Another parameter correlation coefficient signifies linear dependence within the feature. So if two feature vectors are highly correlated it implies that one has linear dependence on another. Correlation coefficient value 1 signifies that the vectors are positively correlated. Thus the features which has correlation coefficient greater than 0.99 are combined together and mean of them is taken as feature. The proposed feature selection method is described in ***algorithm 2*** therefore, generates features which are highly correlated, having significant information content and variance.

Data: $FEATURE\_VECTOR$ of each image
Result: $A\_REDUCED\_FINAL$
$i := j := k := l := 1;$
$count := 0;$
$n :=$ Number of images in the database;
$m :=$ Number of features in $FEATURE\_VECTOR$;
$M_2 :=$ Number of features in $Feature_{reduced}$;
size:= Size of features in $Feature_{reduced}$;
while $i \leq n$ **do**
  while $j \leq m$ **do**
    $ENTROPY(j) :=$ Entropy of the jth feature vector;
  end
  $Feature_{new} :=$ New set of m feature vectors arranged in descending order;
  while $k \leq m$ **do**
    $VAR(k) :=$ Variance of the kth feature of $Feature_{new}$;
    if $VAR(k) < th\_var$ *and* $ENTROPY(k) < th\_entrp$ **then**
      Discard kth feature;
    end
  end
  $Feature_{reduced} :=$ new set of features after discarding ;
  for p :=1 *to size* **do**
    for q :=1 *to size* **do**
      $C(p, q) :=$ Correlation coefficient between pth and qth features;
      if $C(p, q) > 0.99$ *and* $p! = q$ **then**
        $COMBINE$:=Combine pth and qth feature;
        $count = count + 1;$
      end
    end
  end
  for j := 1 *to* $L - count$ **do**
    $A(j) := Feature_{reduced}(j);$
  end
  for $j := (L - count) + 1$ *to* L **do**
    $A(j) := COMBINE(j);$
  end
  $A\_REDUCED\_FINAL(i) := A;$
end

Algorithm 2: Algorithm for Dimension Reduction

5. RESULTS AND DISCUSSIONS

5.1 Databases

Database 1:
CMU Pose, Illumination, and Expression (PIE) Database[17] [16] is a benchmark database containing 41,368 response images of 68 people. Every individual was imaged under 13 different poses, 43 different illumination conditions, and 4 different expressions. To obtain a wide variation in pose, 13 cameras are used and 9 placed roughly at head heights along an arc from left to right. Each pair of these cameras are approximately 22.5^o apart capturing the full left profile to full right profile. Two cameras are placed below and above the frontal camera and two more cameras are placed in the corners of the room which would be a typical position of a surveillance camera. A single image from each of these 13 cameras are captured when a person looks at the front camera with a neutral expression. It resulted 13 different poses of an individual, shown in *figure 4* except the frontal face image.

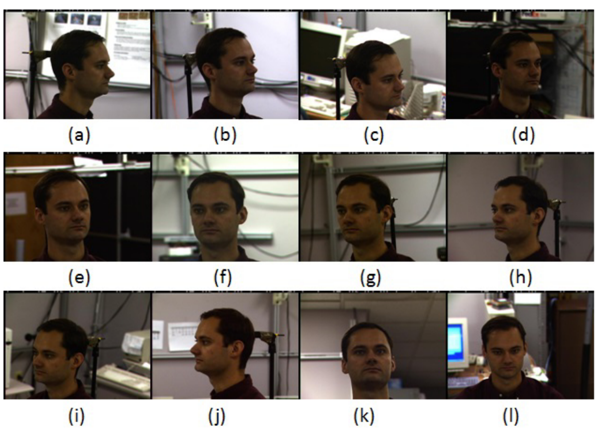


Figure 4: An example of pose variation. The pose varies from full left profile to full right profile each separated by approximately 22.5^o.Last 2 images ((k) and (l)) are taken from 2 cameras above and below the central cameras.Different class labels are marked as Class1:(a), Class2:[(b)-(c)], Class3:(d), Class4:(e), Class5:[(f)-(g)], Class6:[(h)-(i)], Class7:(j)

Database 1 consists of 10 images taken from left and right profile of 38 individuals randomly chosen from CMU PIE database resulting a total of 380 non-frontal face images (190 images from each profile). Since our objective is to recognize faces having different head pose, we have ignored the Illumination and Expression part of the CMU-PIE database. Few instances of the database are given in *figure 5*.

Database 2:
The Head Pose Image Database [8] is a Benchmark of 2790 face images of 15 persons with variations of pan and tilt angles from -90^o to $+90^o$. For every person, 2 series of 93 images (93 different poses) are available. People in face image database with glasses or without glasses and have various skin color. Background is considered neutral in order to focus on face only. Among these images we have chosen

Figure 5: Example from CMU-PIE face image Database (Database 1)

30 different poses of 15 individuals resulting 450 face images to construct ***Database 2*** (225 images from each profile). The poses having a variation over pan angle $+90^o$ to -90^o and tilt angle -15^o to $+15^o$ are considered since number of person is limited. Few instances of the database are given in *figure 6*

Figure 6: Example from Head Pose Image Database (Database 2)

5.2 Clustering for Class Labels

To assign class labels to different training images first we apply K-Means clustering algorithm. Number of clusters vary from 6 to 8 depending on the data set. As a next step images are assigned to different class labels and a valid classifier is chosen for recognition of the face image. It has been observed that manual selection of class labels provide inferior performance compare to assigning class labels through clustering.

5.3 Choice of Classifier

For choosing a valid classifier among different classifiers (like Bayes, SMO and Random Forest), we have used some statistical measures. The statistical measures taken under consideration are Kappa Statistic, area under ROC Curve, and FP rate.

The Kappa value is a metric that compares an Observed Accuracy with accuracy of a random classifier as measured with reference to Expected Accuracy. A good classifier must have a Kappa value greater than 0.7. The value of the area under Receiver Operating Characteristics Curve(ROC Curve) is a metric to determine a good classifier for a particular data set. A good classifier must have ROC area value greater than 0.7. The rate of False Positive (FP) value of a classifier denotes number of instances falsely classified as a given class, indicates miss-classification. Based on these statistical parameters(Kappa statistic, ROC curve), we have chosen the SMO classifier as the actual valid classifier for the data set. A good classifier must have ROC area value greater than 0.7. *Figure7* shows the ROC curves for different classes of Database 1.

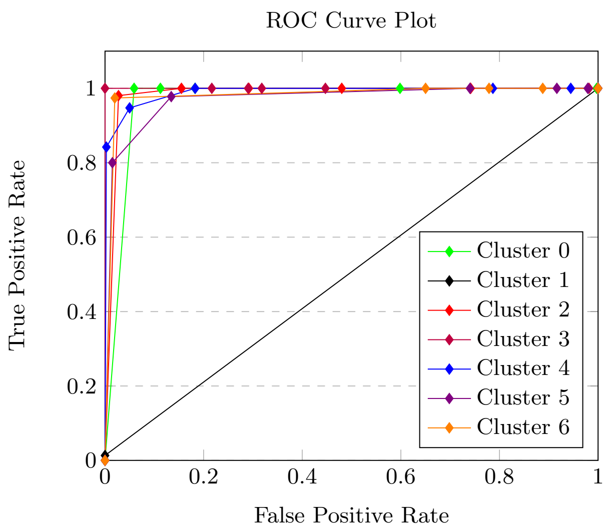


Figure 7: ROC Curve Plot for different classes of Database 1 with Clustering

Table1 shows the statistical measures of different classifiers obtained using WEKA Tool[9]. To obtain classification accuracy we have applied 10-fold cross validation technique on the feature set of 380 face images of Database 1 and 450 face images of Database 2. The overall accuracy is given in *Table2* which shows the comparison of the accuracy and error(in terms of FP rate) of face recognition using the traditional Gabor filter method and the proposed method. Here, traditional Gabor Filter method is considered as the Gabor filtered output where no dimension reduction strategy is apllied thus data dimensionality is very high nearly 4 times of our reduced dataset.

The graph in *figure8* depicts the variation in accuracy with the number of given class labels. From *figure8* it is easily derivable that the class labels assigned by K-Means clustering algorithm provide better result compare to classification without clustering.

A comparison of recognition rate of our test result with various other existing face recognition methods[2][5][22] applied on CMU-PIE database is shown in *table3*, demonstrating better performance than most of the existing methods.

Name of Classifier	Measures	Left profile	Right Profile	Full Database
Bayes	Kappa value	0.8026	0.50	0.63
	ROC Curve	0.90	0.78	0.91
	FP Rate	0.039	0.188	0.05
	Accuracy	84.2105%	70.7692%	70%
SMO	**Kappa value**	**0.8882**	**0.739**	**0.77**
	ROC Curve	**0.97**	**0.88**	**0.95**
	FP Rate	**0.022**	**0.108**	**0.03**
	Accuracy	**91.0526%**	**85.13%**	**81.4%**
Random Forest	Kappa value	0.842	0.44	0.65
	ROC Curve	0.98	0.89	0.94
	FP Rate	0.032	0.321	0.06
	Accuracy	87.3684%	71.2881%	71%

Table 1: Different statistical measure to select valid classifier, which is SMO

Database	Accuracy(%)		FP Rate	
	Traditional Gabor filter	Proposed Method	Traditional Gabor filter	Proposed Method
Database1	92.3684	94.4737	0.021	0.01
Database2	93.3333	95.5556	0.027	0.011

Table 2: The Accuracy of the databases

6. CONCLUSIONS

The proposed method performs better than the existing methods when applied on different databases. Hence this proposed method is flexible in terms of head-pose movement. To prepare the training data set assignment of class labels through clustering provides excellent performance given in the graph shown in *figure8*. By analysing different statistical parameters kernel based SMO classifier is chosen as valid classifier. Our earlier work based on Interpolation method provided 94.3% classification accuracy but costly in terms of computational complexity. Finally, feature selection pro-

Methods	**Accuracy(%)**
PCA	58
Gabor PCA	54.5
LDA	59.5
Gabor LDA	65.5
ICA	59
Gabor Supervised LPP	74.3
Global DCT	44.1
Loca DCT + Feature Fusion	70.9
Local DCT + Decision Fusion	68.5
Proposed Method	**94.4737**

Table 3: Comparison between existing methods and the proposed method using CMU-PIE database

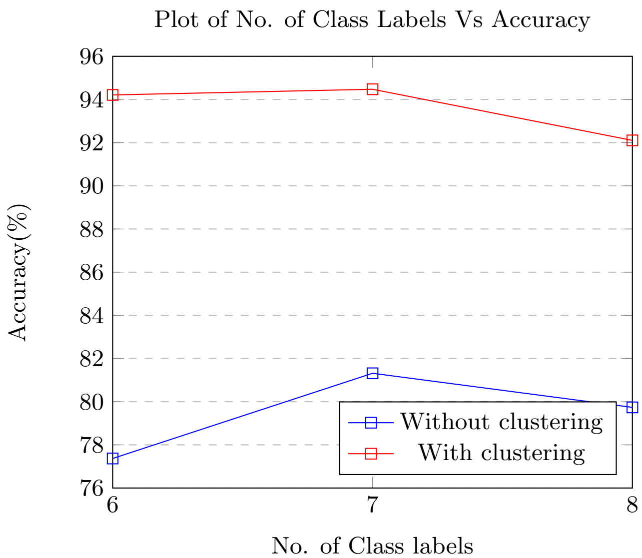


Figure 8: Accuracy of Database 1 with clustering, without clustering

cedure is robust and reduction of feature dimension has significant impact on the result.

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