Strategies for Multi-View Face Recognition for Identification of Human Faces: A Review

Pritesh G. Shah

Department of Computer Science
Mahatma Gandhi Shikshan Mandal's,
Arts, Science and Commerce College, Chopda
Dist: Jalgaon (M.S)
pritshah143@gmail.com

Dr. R.R.Manza

Department of Computer Science and IT
Dr. Babasaheb Ambedkar Marathwada University
Aurangabad.
manzaramesh@gmail.com

***Abstract*— Identity verification of authentic persons by their Multi-view faces is a real valued problem in machine vision. Multi-view faces are having difficulties due to non-linear representation in the feature space. The task of face recognition has been actively researched in recent years. This paper provides an up-to-date review of major human face recognition research. We first present an overview of face recognition and its applications. Then, a literature review of the most recent face recognition techniques is presented. Description and limitations of face databases which are used to test the performance of these face recognition algorithms are given. A large scale evaluation of automatic face recognition technology, and its conclusions are also given. Finally, we give a summary of the research results. This paper critically reviews and summarizes most of these techniques and show sample face recognitions techniques results with percentage of correct classification factor on corresponding face databases.**

***Keywords*— Multi-view face Recognition, Gabor wavelets, global feature extraction, local feature extraction, Gabor wavelet.**

I. Introduction

Digital Image Processing (DIP) is an emerging field of research for computer science researchers. It has got wide range of applications areas like face recognition, medical sciences, remote sensing, weather forecasting, robotics etc. Since scientists have taken up challenge to provide vision, it has become necessary to provide computer the ability to analyse as well as process images. Digital Image Processing does it all for the computers.

The Process of storing an image in computer is known as the problem of image presentation. Computer stores any image in the digital form in any of the four forms viz. Colour image, grayscale image, binary or black and white image, or image may be stored using image properties. The natural world pictures are generally in colour mode where hundreds or thousands of colours are used. Normally the medical images like x-ray images and MRI images are in grayscale form. Some of the applications use images or pictures made in only two colours black and white. Such application preserve images in binary or black and white form. Sometimes the images are created using geometrical shapes. Such images can be stored easily using the properties of image.

As mentioned earlier image processing is done on any image primarily for improving the quality of any image or for some specific purpose like edge detection or motion detection. Many times, specially for providing vision to computers, the computer needs difference between two different objects. This requires analysis and understanding of the image. Many applications require counting say how many different objects are there or what types of objects are there in an image. This problem requires segmentation to be performed. This problem is widely known as Image Recognition, where colours, objects, shapes, texture, patterns etc are recognized.

Face recognition is an important research problem spanning numerous fields and disciplines. This because face recognition, in additional to having numerous practical applications such as bankcard identification, access control, security monitoring, and surveillance system, is a fundamental human behavior that is essential for effective communications and interactions among people. The rapid development of face recognition is due to a combination of factors: active development of algorithms, the availability of large databases of facial images, and a method for evaluating the performance of face recognition algorithms.

In the literatures, face recognition problem can be formulated as: given static (still) or video images of a scene, identify or verify one or more persons in the scene by comparing with faces stored in a database.

Face recognition starts with the detection of face patterns in sometimes cluttered scenes, proceeds by normalizing the face images to account for geometrical and illumination changes, possibly using information about the location and appearance of facial landmarks, identifies the faces using appropriate classification algorithms, and post processes the results using model-based schemes and logistic feedback [1].

All face recognition algorithms consistent of two major parts: (1) face detection and normalization and (2) face identification. Algorithms that consist of both parts are referred to as fully automatic algorithms and those that consist of only the second part are called partially automatic algorithms. Partially automatic algorithms are given a facial image and the coordinates of the center of the eyes. Fully automatic algorithms are only given facial images.

Focusing on the aspect of pose invariance, face recognition approaches may be divided into two categories: (i) global approach and (ii) component-based approach. In global approach, a single feature vector that represents the whole face image is used as input to a classifier. Several classifiers have been proposed in the literature e.g. minimum distance classification in the eigenspace [2], Fisher's discriminant analysis, and neural networks. Global techniques work well for classifying frontal views of faces. However, they are not robust against pose changes since global features are highly sensitive to translation and rotation of the face. To avoid this problem an alignment stage can be added before classifying the face. Aligning an input face image with a reference face image requires computing correspondence between the two face images. The correspondence is usually determined for a small number of prominent points in the face like the center of the eye, the nostrils, or the corners of the mouth. Based on these correspondences, the input face image can be warped to a reference face image.

Current systems work very well whenever the test image to be recognized is captured under conditions similar to those of the training images.

We may categorize approaches used to deal with variation in appearance into three kinds: invariant features, canonical forms, and variation- modeling. The first approach seeks to utilize features that are invariant to the changes being studied. For instance, the Quotient Image [3] is invariant to illumination and may be used to recognize faces when lighting conditions change. The second approach attempts to "normalize" way the variation, either by clever image transformations or by synthesizing a new image (from the given test image) in some "canonical" or "prototypical" form. Recognition is then performed using this canonical form. The third approach of variation-modeling usually leads to some parameterization of the subspace(s). Recognition is then performed by choosing the subspace closest to the test image, after the latter has been appropriately mapped. In effect, the recognition step recovers the variation (e.g. pose estimation) as well as the identity of the person. For examples of this technique, see [4].

A feature invariant to illumination works well as long as pose or facial expression remains constant, but fails to be invariant when pose or expression is changed [4].

We can make two important observations after surveying the research literature: (1) there does not appear to be any feature, set of features, or subspace that is simultaneously invariant to all the variations that a face image may exhibit, (2) given more training images, almost any technique will perform better. These two factors are the major reasons why face recognition is not widely used in real-world applications. The fact is that for many applications, it is usual to require the ability to recognize faces under different variations, even when training images are severely limited.

However, face recognition with Multi-view faces is still be a challenged for invariant and robust recognition. In Multi-view face recognition system, difficulties occurred due to non-linear representation in feature spaces. To minimize the demerits that often occur in Multi-view faces, a global representation to non-linear feature spaces is necessary. In addition, variations in facial expressions, lighting conditions, occlusions, un-suitable environments, and unwanted noises, affine distortions, clutter, etc, may also give some bad impact on the overall performance of face recognition accuracy. To ensure robust recognition of

Multi-view faces with high recognition rate, some remarkable strategies proposed in [5-6].

II. REVIEW OF FACE RECOGNITION TECHNIQUES

This section gives an overview on the major human face recognition techniques that apply to Multi-view face recognition and frontal faces, advantages and disadvantages of each method are also given. The methods considered are principal component analysis, Gabor wavelet, SVM-based Multi-view Face Recognition by Generalization of Discriminant Analysis, neural networks, and template matching. The approaches are analyzed in terms of the facial representations they used.

A. Feature Extraction Methods

1) Global feature extraction

Principal component analysis (PCA) method used for global feature extraction is a powerful technique for extracting global structures from high-dimensional data set and has been widely used to reduce dimensionality and extract abstract features of faces for face recognition (Turk and Pentland, 11; Zhao et al., 2000). Principal component analysis (PCA) uses to reduce the high dimensionality feature space to the smaller intrinsic dimensionality of feature space. In mathematical terms, eigenfaces are the principal components of the distribution of faces, or the eigenvectors of the covariance matrix of the set of face images. The eigenvectors are ordered to represent different amounts of the variation, respectively, among the faces. Each face can be represented exactly by a linear combination of the eigenfaces.

The main idea of using PCA [7] for face recognition is to express the large 1-D vector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors). PCA based approaches typically include two phases: training and classification. In the training phase, an eigenspace is established from the training samples using PCA and the training face images are mapped to the eigenspace for classification. In the classification phase, an input face is projected to the same eigenspace and classified by an appropriate classifier.

Reference [8] extended their early work on eigenface to eigenfeatures corresponding to face components, such as eyes, nose, and mouth. They used a modular eigenspace which was composed of the above eigenfeatures (i.e., eigeneyes, eigennose, and eigenmouth). This method would be less sensitive to appearance changes than the standard eigenface method. The system achieved a recognition rate of 5 percent on the FERET database of 7,562 images of approximately 3,000 individuals. In summary, eigenface appears as a fast, simple, and practical method. However, in general, it does not provide invariance over changes in scale and lighting conditions.

[9] proposes a classification-based face detection approach using Gabor filter features. Four Gabor filters are designed for facial feature extraction and the feature vector based on Gabor filters is applied to be the input of the classifier. The underlying classifier is a polynomial neural network (PNN) on a reduced feature subspace learned by PCA. The detection performances of different parts of Gabor representations have been investigated. The effectiveness of the proposed method is justified in experiments on testing a large number of images.

It also states that methods for face detection generally fall into two categories: feature-based methods and classification based methods. Out of which feature-based methods detect faces by searching for facial features (eyes, nose and mouth) and grouping them according to their geometrical relationships (Lin and Fan 2001; Wong et al., 2001). Since the performance of feature-based methods primarily depends on the reliable location of facial features, it is susceptible to partial occlusion, excessive deformation, and low quality of images. By classification-based methods, face detection is performed by shifting a search window over the input image and each local image in the window is classified to face/non-face class using a classifier. As such, the feature extraction from local images and the design of classifier are important to the detection performance.

B. Local feature analysis

1) Linear Discriminant Analysis

As main facial features, eyes, nose and mouth often show the most distinguishable information of a given individual. However, it is very hard for computers to form a stable geometrical representation as we describe a face in our daily life. These sub-regions of face images are very small, so we adopt two-dimensional Wavelets analysis to create a representation of facial features in the framework.

We take Gabor wavelets as the basis function to create this representation, because Gabor wavelets have been used extensively in image processing, texture analysis due to their biological relevance and computational properties. Gabor wavelets can capture the properties of spatial localization, orientation selectivity, spatial frequency selectivity and quadrature phase relationship. Its representation has been shown to be optimal for minimizing the joint two-dimensional uncertainty in space and frequency (Daugman, 188; He et al., 2002; Burr et al., 18). The face's Gabor wavelets representation has robust characteristics in illumination and facial expression changes.

The method introduced in [10] is to combine Global feature vectors (PCA-transformed) and local feature vectors (Gabor wavelet-transformed) via complex vectors as input feature of improved LDA which is to safely remove the null space of the between-class scatter matrix and to utilize the properties of Hermitian matrix. The effectiveness of the proposed method (GLU-LDA) has been demonstrated through experimentation using popular face database such as ORL which consisted of 400 frontal faces: 10 tightly cropped images of 40 subjects with variations. And UMIST (Graham *et al.*, 18) repository is a multi-view database, consisting of 575 images of 20 people, each covering a wide range of poses from profile to frontal views.

Gabor wavelet has extensively been studied in biometrics, such as in face, fingerprint and palm print biometrics. Due to its strong representation capability, Gabor wavelet transform is still be a feature extraction tool for some pattern recognition and biometric applications. Fundamentally, 2D Gabor filter refers a linear filter whose impulse response function defines as the multiplication of harmonic function and Gaussian function. The Gaussian function is modulated by a sinusoid function.

For Gabor face representation, face image convolves with the Gabor wavelet transform for capturing substantial amount of variations among face images in the spatial locations. Gabor wavelet transforms with five frequencies and eight orientations use for generation of 40 spatial frequencies and for Gabor face extraction. In practice, Gabor face responses having very long representation vectors and the dimension of Gabor feature vector is prohibitively large. Due to huge dimensionality of Gabor responses, dimensionality reduction operation is performed using canonical covariate.

The generalization of LDA i.e., the canonical variate used to project a dataset onto the sub-space and it shows lower variance, but classification probability is very high. Due to useful characteristics of Gabor responses, its representation is more robust and effective against varying brightness and contrast in the face image. With this representation, the Gabor canonical face responses remove some shortcomings. Due to the pose, illumination, expressions etc.

A new method for face recognition has been introduced in [11] which combines kernel-based methodologies with discriminant analysis techniques. The kernel function is utilized to map the original face patterns to a high-dimensional feature space, where the highly complex distribution of face patterns is linearized and simplified, so that linear discriminant techniques can be used for feature extraction. The “small sample size” (SSS) problem caused by high dimensionality of mapped patterns, is addressed by an improved D-LDA technique. The new algorithm has been tested in terms of error rate performance, on the multi-view UMIST Face Database. Experimental results indicate that the performance of the KDDA algorithm is overall superior to that obtained by the KPCA or GDA approaches.

2) Neural Networks

The attractiveness of using neural networks could be due to its non linearity in the network. Reference [12] proposed a hybrid neural network which combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network. The SOM provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimension reduction and invariance to minor changes in the image sample. The convolutional network extracts successively larger features in a hierarchical set of layers and provides partial invariance to translation, rotation, scale, and deformation. The authors reported 6.2% correct recognition on ORL database of 400 images of 40 individuals.

Probabilistic decision-based neural network (PDBNN) based biometric identification system has the merits of both neural networks and statistical approaches, and its distributed computing principle is relatively easy to implement on parallel computer. In [13], it was reported that PDBNN face recognizer had the capability of recognizing up to 200 people and could achieve up to 6% correct recognition rate in approximately 1 second. However, when the number of persons increases, the computing expense will become more demanding. In general, neural network approaches encounter problems when the number of classes (i.e., individuals) increases. Moreover, they are not suitable for a single model image recognition test because multiple model images per person are necessary in order for training the systems to “optimal” parameter setting.

The feature vector based on Gabor filters used as the input of the classifier, which is a Feed Forward Neural Network (FFNN) on a reduced feature subspace learned by an approach simpler than Principal Component Analysis (PCA). The MLP (Multi-layer Perceptron) algorithm is used to classify face and non-face patterns before the recognition step.

A new approach to face detection with Gabor wavelets & feed forward neural network is presented in [14]. The method uses Gabor wavelet transform & feed forward neural network for both finding feature points and extracting feature vectors. From the experimental results, it is seen that proposed method achieves better results compared to the graph matching and eigenfaces methods, which are known to be the most successive algorithms. [14] also implements Artificial Neural Network(ANN) algorithm and design of Gabor filter in order to provide better image classification. The MLP (Multi-layer Perceptron) algorithm is used to classify face and non-face patterns before the recognition step.

In [15] the Gabor filter bank is used to extract facial features that characterized by spatial frequency, spatial locality and orientation. Gabor face representation captures substantial amount of variations of the face instances that often occurs due to illumination, pose and facial expression changes. Convolution of Gabor filter bank to face images of rotated profile views produce Gabor faces with high dimensional features vectors. Canonical covariate is then used to Gabor faces to reduce the high dimensional feature spaces into low dimensional subspaces. Finally, support vector machines are trained with canonical sub-spaces that contain reduced set of features and perform recognition task. The proposed system is evaluated with UMIST face database. The experiment results demonstrate the efficiency and robustness of the proposed system with high recognition rates.

Performance of the proposed system estimated as a robust face recognition system when it compared with the other methods presented in [15]. Reported results confirm the efficacy of the proposed scheme while the method tested on the UMIST dataset with quite complex multi-view faces. The performance largely dependent on three factors: the dataset to be uses, combined feature representation scheme and the right classifier. The present system [15] can combat with various problems and classify faces efficiently.

3) Graph Matching

Graph matching is another approach to face recognition.

The matching process is computationally expensive, taking about 25 seconds to compare with 87 stored objects on a parallel machine with 23 transputers. Reference [16] extended the technique and matched human faces against a gallery of 112 neutral frontal view faces. Probe images were distorted due to rotation in depth and changing facial expression. Encouraging results on faces with large rotation angles were obtained. They reported recognition rates of 86.5% and 66.4% for the matching tests of 111 faces of 15 degree rotation and 110 faces of 30 degree rotation to a gallery of 112 neutral frontal views. In general, dynamic link architecture is superior to other face recognition techniques in terms of rotation invariance; however, the matching process is computationally expensive.

4) Template Matching

A simple version of template matching is that a test image represented as a two-dimensional array of intensity values is compared using a suitable metric, such as the Euclidean distance, with a single template representing the whole face.

In [17], Bruneli and Poggio automatically selected a set of four features templates, i.e., the eyes, nose, mouth, and the whole face, for all of the available faces.

One drawback of template matching is its computational complexity. Another problem lies in the description of these templates. Since the recognition system has to be tolerant to certain discrepancies between the template and the test image, this tolerance might average out the differences that make individual faces unique.

5) Support Vector Machine (SVM)

A Support Vector Machine (SVM) face identification method using optimized Gabor features is presented in [18] which uses a boosting algorithm to find the most significant positions and wavelet to extract features for face recognition. The features thus extracted are efficient. By combining boosting selected Gabor features with SVM, our method not only substantially reduces computation and memory cost of the feature extraction process, but also achieves the same performance as that of down sample Gabor + LDA, when FERET database is used for testing.SVM can also be viewed as a way to train polynomial neural networks.

In summary, the main characteristics of SVMs are: (1) that they minimize a formally proven upper bound on the generalization error; (2) that they work on high-dimensional feature spaces by means of a dual formulation in terms of kernels; (3) that the prediction is based on hyperplanes in these feature spaces, which may correspond to quite involved classification criteria on the input data; and (4) that outliers in the training data set can be handled by means of soft margins.

In [19], the face recognition problem is formulated as a problem in difference space, which models dissimilarities between two facial images. In different space they formulate face recognition as a two class problem. The cases are: (i) Dissimilarities between faces of the same person, and (ii) Dissimilarities between faces of different people. The SVM-based algorithm is compared with a principal component analysis (PCA) based algorithm on a difficult set of images from the FERET database. Performance was measured for both verification and identification scenarios. The identification performance for SVM is 77-78% versus 54% for PCA. For verification, the equal error rate is 7% for SVM and 13% for PCA.

A Support Vector Machine based multi-view face detection and recognition framework is described in [20]. Face detection is carried out by constructing several detectors, each of them in charge of one specific view. The symmetrical property of face images is employed to simplify the complexity of the modeling. The estimation of head pose, which is achieved by using the Support Vector Regression technique, provides crucial information for choosing the appropriate face detector. This helps to improve the accuracy and reduce the computation in multi-view face detection compared to other methods.

6) *Multiple Classifier Systems (MCSs)*

Reference [21] presents a system for invariant face recognition. A combined classifier uses the generalization capabilities of both LVQ and Radial Basis Function (RBF) neural networks to build a representative model of a face from a variety of training patterns with different poses, details and facial expressions. The combined generalization error of the classifier is found to be lower than that of each individual classifier. A new face synthesis method is implemented for reducing the false acceptance rate and enhancing the rejection capability of the classifier. The system is capable of recognizing a face in less than one second. The well-known ORL database is used for testing the combined classifier. In the case of the ORL database, a correct recognition rate of .5% at 0.5% rejection rate is achieved.

[22] provides a general feature extraction method for multi-view face detection. We present a recursive nonparametric discriminant analysis, based on traditional Fisher discriminant analysis and nonparametric discriminant analysis, to extract features for more general distributions with moderate requirement of training samples and running time. Probabilistic classifiers are then learned from feature distributions. Multiple classifiers are combined together using AdaBoost to form a multi-view face classifier.

The RNDA feature extraction method can handle more general class distributions than Fisher discriminant analysis, and can reduce the computational complexity of nonparametric discriminant analysis, so it performs well for the profile face and eye detection Experimental results both on the multi-view face detection and on the eye detection demonstrate RNDA feature's success in handling various patterns. Although the discriminant features are more computationally expensive than Haar features, the speed problem can be tackled by using Haar features as frontal end of a cascade. The future work will focus on further improving the speed.

III. COMPARISON OF DIFFERENT FACE DATABASES

In Section 2, a number of face recognition algorithms have been described. In Table I, we give a comparison of face databases which were used to test the performance of these face recognition algorithms. While existing publicly-available face databases contain face images with a wide variety of poses, illumination angles, gestures, face occlusions, and illuminant colors, these images have not been adequately annotated, thus limiting their usefulness for evaluating the relative performance of face detection algorithms. For example, many of the images in existing databases are not annotated with the exact pose angles at which they were taken. In order to compare the performance of various face recognition algorithms presented in the literature there is need for a comprehensive, systematically annotated database populated with face images that have been captured (1) at variety of pose angles (to permit testing of pose invariance), (2) with a wide variety of illumination angles (to permit testing of illumination invariance), and (3) under a variety of commonly encountered illumination color temperatures (permit testing of illumination color invariance). Reference [23] presents a methodology for creating such an annotated database that employs a novel set of apparatus for the rapid capture of face images from a wide variety of pose angles and illumination angles. Four different types of illumination are used, including daylight, skylight, incandescent and fluorescent. The entire set of images, as well as the annotations and the experimental results, is being placed in the public domain, and made available for download over the worldwide web [24]. The description and limitations of each database are given [25].

Face recognition is one of the most important applications of Gabor wavelets. The face image is convolved with a set of Gabor wavelets and the resulting images are further processed for recognition purpose. The Gabor wavelets are usually called Gabor filters in the scope of applications. There are many other application of Gabor wavelets, such as the facial expression classification [26,27], Gabor networks for face reconstruction [28], fingerprint recognition [29], facial landmark location [30], and iris recognition [31], etc.

In [32], technique is proposed which makes the use of a Gabor Filter Bank to extract an augmented Gabor-face vector to solve the pose estimation problem, extract some statistical features such as means and variances. And then the classification is performed using the nearest neighbour algorithm with the Euclidean distance.

[32] also introduces a Gabor Wavelet Classification method for face recognition. The processing of facial images by a Gabor filter is chosen for its biological relevance and technical properties. The Gabor filter kernels have similar shapes as the receptive fields of simple cells in the primary visual cortex [33]. They are multi-scale and multi-orientation kernels. The Gabor transformed face images yield features that display scale, locality, and differentiation properties. These properties are quite robust to variability of face image formation, such as the variations of illumination, head rotation and facial expressions.

In this paper we have proposed a method for face recognition based on Gabor Filter Banks. We have shown that a Gabor filter yields robustness against expression, illumination and small rotations. This has been demonstrated by a recognition rate of 93% even by using very simple statistical features such as means and variances and a basic metric such as Euclidean distance.

Much progress has been made towards recognizing faces under controlled conditions [34],[35] (especially for faces under normalized pose and lighting conditions and with neutral expression). However, recognition of face images acquired in an outdoor environment with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system.

7. *Local Gabor Binary Patterns (LGBP)*

The multi-view face representation is based on Local Gabor Binary Patterns (LGBP) and encodes the local facial characteristics in to a compact feature histogram in [36]. In LGBP, the Gabor filters with 8 different orientations can reflect the orientation of heads in the multi-view face images, and then the Local Binary Patterns (LBP) [37] operator based on the Gabor features can reflect the local information on the different orientations and different scales. The combination of Gabor and LBP further enhance the representation power of the multi-view face images greatly. LGBP is first used for face recognition and attain the impressive result on FERET database [38]. It is concluded here that three or less orientation in LGBP may have the better results in pose estimation. But, the dimensions are reduced greatly.

[39] Focuses on Face recognition under varying lighting conditions is challenging, especially for single image based recognition system. Exacting illumination invariant features is an effective approach to solve this problem. However, existing methods are hard to extract both multi-scale and multi-directivity geometrical structures at the same time, which is important for capturing the intrinsic features of a face image. Here, it is propose to utilize the logarithmic nonsubsampled contourlet transform (LNSCT) to estimate the reflectance component from a single face image and refer it as the illumination invariant feature for face recognition, where NSCT is a fully shift-invariant, multi-scale, and multi-direction transform. LNSCT can extract strong edges, weak edges, and noise from a face image using NSCT in the logarithm domain.

The approaches of solving illumination problem in face recognition can be generally summarized into three categories: First, [40]: preprocessing and normalization technique [41], Second, face modeling [42], and Third, invariant feature extraction [43, 44]. Methods of preprocessing and normalization process face image using image processing techniques, such as histogram equalization(HE),to normalize face image such that it appears to best able under different lighting conditions. These approaches are always easy to implement, but it is still hard to obtain notable improvement for recognition. The model-based approach attempts to construct a generative 3-D face model that can be used to render face images of different poses and under varying lighting conditions. In these methods, a number of training samples are required and many assumptions are always made. Compared with the other two approaches, extracting illumination invariant features is a more effective approach for face recognition under various lighting conditions. Representative methods include local binary patterns (LBP), Gabor feature, self quotient image (SQI), logarithmic total variation (LTV) [43], and logarithmic wavelet transform (LWT) [44]. Recently, with the similar kernels of Gabor wavelet, the dual-tree complex wavelet transform (DT-CWT) [45] is used for face representation. DT-CWT is good at capturing directional selective features in six different fixed orientations at dyadic scales and outperforms Gabor due to less redundancy and more efficient computation.

V. CHALLENGES INVOLVED IN FACE RECOGNITION

It has been observed that “the variations between the images of the same face due to illumination and viewing direction are almost always larger than image variations due to change in face identity” [46].

The problem of face recognition can be cast as a standard pattern classification or machine learning problem: Given a set of face images labeled with the person's identity (the gallery set) and an unlabeled set of face images from the same group of people (the probe set), we seek to identify each person in the probe images.

This problem is attacked in three steps. In the first step, the face is located in the image; this process, known as face detection, is in many respects as challenging a problem as face recognition, see [47, 48] for more detail. In the second step, a collection of descriptive measurements known as a feature vector is extracted from each image. In the third step, a classifier is trained to assign to each feature vector a label with a person’s identity. (Note that these classifiers are simply mathematical functions which, given a feature vector, return an index corresponding to a subject’s identity.)

V. SUMMARY OF THE RESEARCH RESULTS

In Table I, a summary of performance evaluations of face recognition algorithms on different databases is given.

Database	Description	Method	Percentage of correct classification(PCC)
FERET	Contains face images of over 1000 people. It was created by the FERET program, which ran from 13 through 17. It contains many images of the same people taken with time-gaps of one year or more, so that some facial features have changed. This is important for evaluating the robustness of face recognition algorithms over time.	Eigenface	5% , 85% , 64% correct classifications averaged over lighting, orientation, and size variation, respectively.
		Graph Matching	86.5% and 66.4% for the matching tests of 111 faces of 15 degree rotation and 110 faces of 30 degree rotation to a gallery of 112 neutral frontal views
		SVM	Identification performance is 77.78% versus 54% for PCA. Verification performance is 3%versus 87% for PCA.
UMIST	Consists of 564 images of 20 people. Each covering a range of poses from profile to frontal views. Subjects cover a range of race/sex/appearance. Each subject exists in their own directory labeled 1a, 1b, 1t and images are numbered consecutively as they were taken. The files are all in PGM format, approximately 220 x 220 pixels in 256 shades of grey.	SVM	Efficient and robust with high recognition rates [15].
ORL	Ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).	Eigenface	90%.
AR	4,000 color images corresponding to 126 people's faces (70 men and 56 women). Images feature frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf).	SVM+PCA SVM+ICA	2.67% SVM was used only with polynomial (up to degree 3) And Gaussian kernel. 4%
Yale	frontal grayscale face images of 15 people, with 11 face images of each subject, giving a total of 165 images. Lighting variations include left-light, center-light, and right-light. Spectacle variations include with-glasses and without-glasses. Facial expression variations include normal, happy, sad, sleepy, surprised, and wink.	Build face recognition committee machine (FRCM) of Eigenface, Fisherface, Elastic Graph Matching (EGM), SVM, and Neural network	FRCM gives 86.1% and it outperforms all the individuals on average.

Acknowledgment

Author wishes to thanks his Parents, Dr. Suresh G. Patil, Founder President, Adv. Sandeep Suresh Patil, President, Dr. Smita S. Patil, Secretary, MGSM, Chopda, Dr. D. D. Patil, Principal, Dr. A.L. Chaudhari Head of Computer & Electronics Department, Asst. Prof. Mrs. P.M. Patil, Arts, Science & Commerce College, Chopda Dist. Jalgaon, Maharashtra India for giving the cooperation during the research work.

REFERENCES

[1] R. Chellappa, C.L. Wilson and C. Sirohey,"Human and machine recognition of faces: A survey," *Proc. IEEE*, vol. 83, no. 5, pp. 705- 740, may 15.

[2] M. Turk and A. Pentland "Face recognition using eigenfaces," In *Proc. IEEE Conference* on *Computer Vision and Pattern Recognition*, pp. 586–591, 1991.

[3] T. Riklin-Raviv and A. Shashua, "The Quotient image: Class based recognition and synthesis under varying illumination conditions," *In CVPR*, P. II: pp. 566-571, 1.

[4] A.S. Georghiades, P.N. Belhumeur, and D.J. Kriegman, "From few to many: Generative models for recognition under variable pose and illumination," In *AFGR*, 2000.

[5] M. S. Bartlett, J. R. Movellan, and T. J. Sejnowski, "Face recognition by independent component analysis," *IEEE Transaction on Neural Networks*, vol. 13, no. 6, pp. 1450 – 1464, 2002.

[6] M. H. Yang, "Kernel eigenfaces vs. kernel fisherfaces: Face recognition using kernel methods," Proceedings of the Fifth IEEE

[7] M. Dai, and M. Q. Zhou, "On automatic human face recognition," *Advances Biometrics*, vol. 1, pp. 41 - 48, 2003.

[8] A. Pentland, B. Moghaddam, and T. Starner, "View-Based and modular eigenspaces for face recognition," *Proc. IEEE CS Conf. Computer Vision and Pattern Recognition*, pp. 84-91, 1994

[9] Lin-Lin Huang , Akinobu Shimizu, Hidefumi Kobatake, "Robust face detection using Gabor filter features", Elsevier, Pattern Recognition Letters 26 (2005) 1641–164

[10] *Li et al. / J Zhejiang* , "A novel face recognition method with feature combination" ISSN 100-305 *6A(5):454-45,2005*.

[11] Juwei Lu, K.N. Plataniotis, A.N. Venetsanopoulos, "A kernel machine based approach for multi-view face recognition", IEEE International Conference of Image Processesing, pp. 265-268, 2002

[12] S. Lawrence, C.L. Giles, A.C. Tsoi, and A.D. Back, "Face recognition: A convolutional neural-network approach," *IEEE Trans. Neural Networks*, vol. 8, pp. 98-113, 1997.

[13] S.H. Lin, S.Y. Kung, and L.J. Lin, "Face recognition/detection by probabilistic decision-based neural network," *IEEE Trans. Neural Networks*, vol. 8, pp. 114-132, 1997.

[14] Avinash Kaushal, J P S Raina, "Face Detection using Neural Network & Gabor Wavelet Transform", International Journal of Computer Sci ence and Technology, Vol. 1, Iss ue 1, September 2010.

[15] Dakshina Ranjan Kisku, Hunny Mehrotra, Jamuna Kanta Sing, and Phalguni Gupta, "SVM-based Multiview Face Recognition by Generalization of Discriminant Analysis",International Journal of Intelligent Systems and Technologies, 2008.

[16] L. Wiskott and C. von der Malsburg, "Recognizing faces by dynamic link matching," *Neuroimage, vol.* 4, pp. 514-518, 1996.

[17] R. Bruneli and T. Poggio, "Face recognition: features versus templates," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 15, pp. 1042-1052, 1993.

[18] Linlin SHEN, "Gabor Features and Support Vector Machine for Face Identification", Biomedical Soft Computing and Human Sciences, Vol.14, No.1, pp.61-66 (200)

[19] P.J. Phillips, "Support vector machines applied to face recognition," *Processing system* 11, 1.

[20] Y. Li, S. Gong and H. Liddell. Support vector regression and classification based multi-view face detection and recognition. In Proc. *IEEE International Conference on Face and Gesture Recognition*, Grenoble, France, March 2000.

[21] A.S. Tolba, and A.N. Abu-Rezq, "Combined classifiers for invariant face recognition," *Pattern Anal. Appl*. Vol. 3, no. 4, pp. 289-302, 2000.

[22] Peng Wang , Qiang Ji, "Learning Discriminant Features for Multi-View Face and Eye Detection", Proceedings of theIEEE Computer Society Conference on Computer Vision and Pattern Recognition 2005.

[23] John A. Black, M. Gargesha, K. Kahol, P. Kuchi, Sethuraman Panchanathan," A Framework for performance evaluation of face recognition algorithms," in *Proceedings of the International Conference on ITCOM, Internet Multimedia Systems II*, 2002.

[24] The FacePix reference image set is in the public domain, Available: http://cubic.asu.edu/vccl/imagesets/facepix.

[25] A. S. Tolba, A.H. El-Baz, and A.A. El-Harby, "Face Recognition: A Literature Review", International Journal of Signal Processing Volume 2 Number 2, 2005.

[26] M. Lyons, S. Akamatsu, M. Kamachi, and J. Gyoba, "Coding facial expressions with Gabor wavelets," Proc. Int'l Conf. Automatic Face and Gesture Recognition, 200-205, 1998

[27] Z. Zhang, M. Lyons, M. Schuster, and S. Akamatsu, "Comparison between geometry-based and Gabor-wavelets-based facial expression recognition using multi-layer perceptron," Proc. Int'l Conf. Automatic Face and Gesture Recognition, 454-459, 1998.

[28] V. Kruger and G. Sommer, "Gabor wavelet networks for efficient head pose estimation," Image and Vision Computing, 20(9-10), 665-672, 2002.

[29] C. J. Lee and S. D. Wang, "Fingerprint feature extraction using Gabor filters," Electronic letters, 35(4), 288-290, 1999

[30] F. Smeraldi and J. Bigun, "Facial feature detection by saccadic exploration of the Gabor decomposition", Proc. Int'l Conf. Image Processing, 163-167

[31] C. Sanchez-Avila and R. Sanchez-Reillo, "Two different approaches for iris recognition using Gabor filters and multiscale zero-crossing representation," Pattern recognition letters, 38(2): 231-2440, 2005.

[32] Walid R. Boukabou, Lahouari Ghouti, Ahmed Bouridane, "Face Recognition Using a Gabor Filter Bank Approach", Proceedings of the First NASA/ESA Conference on Adaptive Hardware and Systems, IEEE, 2006.

[33] L. Wiskott, J.M. Fellous, N. Krger, and C. von der Malsburg, "Face Recognition by Elastic Bunch Graph Matching," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, pp. 775-779, 1997.

[34] P. J. Phillips, P. J. Flynn, T. Scruggs, K. W. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek, "Overview of the Face Recognition Grand Challenge," Proc. of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005.

[35] W. Zhao, R. Chellappa, A. Rosenfeld, and P.J. Phillips, "Face recognition: A literature survey," ACM Computing Surveys, Vol. 35, No. 4, Dec. 2003.

[36] Bingpeng Ma, Wenchao Zhang, Shiguang Shan, Xilin Chen, Wen Gao, "Robust Head Pose Estimation Using LGBP", IEEE, 2006.

[37] A. Timo, H. Abdenour and P. Matti, "Face recognition with Local Binary Patterns". The 8th European Conference on Computer Vision, Prague, May 11-14, 2004.

[38] W. Zhang, S. Shan, W. Gao, X. Chen and H. Zhang, "Local Gabor Binary Pattern Histogram Sequence (LGBPHS): A Novel Non-Statistical Model for Face Representation and Recognition". In Proc. of 10th IEEE Int'l Conf. on Computer Vision, Beijing, China, Oct.15-21, 2005.

[39]Xiaohua Xie, JianhuangLai, Wei-ShiZheng, "Extraction of illumination invariant facial features from a single image using nonsubsampled contourlet transform", Journal of Pattern Recognition, Elsevier 2010.

[40] W. Chen, M.J. Er, S. Wu, Illumination compensation and normalization for robust face recognition using discrete cosine transform in logarithm domain, IEEE Transactions on Systems, Man and Cybernetics, Part B 36 (2006) 458–466.

[41] S. Shan, W. Gao, B. Cao, D. Zhao, Illumination normalization for robust face recognition against varying lighting conditions, in: Proceedings of Interna- tional Workshop Analysis and Modeling of Faces and Gestures, 2003.

[42] A. Georghiades, P. Belhumeur, D. Kriegman, From few to many: illumination cone models for face recognition under variable lighting and pose, IEEE Transactions on Pattern Analysis and Machine Intelligence 23 (2001) 643–660.

[43] T. Chen, W. Yin, X. Zhou, D. Comaniciu, T.S. Huang, Total variation models for variable lighting face recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence 28 (2006) 1519–1524.

[44] T. Zhang, B. Fang, Y. Yuan, Y. Tang, Z. Shang, D. Li, F. Lang, Multiscale facial structure representation for face recognition under varying illumination, Pattern Recognition 42 (2009) 251–258.

[45] N.G. Kingsbury, Complex wavelets for shift invariant analysis and filtering of signals, Journal of Applied and Computational Harmonic Analysis 10 (2001) 234–253.

[46] Y. Moses, Y. Adini, and S. Ullman. Face recognition: The problem of compensating for changes in illumination direction. In European Conf. on Computer Vision, pages 286–296, 1994.

[47] P. Viola, M. J. Jones. Robust Real-Time Face Detection. Int. J. Computer Vision 57, 2, pages 137—154. May 2004.

[48] M. Yang, D. J. Kriegman, and N. Ahuja. Detecting Faces in Images: A Survey. IEEE Trans. Pattern Anal. Mach. Intell. 24, 1, pages 34—58. January 2002.