Face Detection and Recognition Techniques: A Quick Overview

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Abstract- *Face recognition of an individual in a crowd is a challenging issue that has received the deserved attention during current scenario. This is a trivial task for brain, but cumbersome to be imitated artificially. The commonalities in faces does pose a problem on various grounds but features such as skin color, gender differentiate a person from the other. This can be attributed to its various applications in different fields such as content-based image retrieval, video coding, video conferencing, crowd surveillance, and intelligent human–computer interfaces. There has been significant contribution to the solution of this problem by various researchers.*

This review paper is a study of various techniques being used for face recognition. A face recognition system includes three steps viz face detection, feature extraction and face recognition. Various recognition techniques and descriptions of representative methods have also been covered. The majority of face recognition methods have been developed by scientists with a very technical background such as biometry, pattern recognition and computer vision. The concepts and practical issues relating to the application of each step of a face recognition system and their various strategies are given, without going into technical details.

Keywords: *Face detection; Recognition; Neural Network; Eigenfaces; Hidden Markov.*

I. Introduction

One of the most relevant applications of image processing is face recognition. It is a challenge to build an automated system that has capabilities similar to humans to recognize faces. Although humans are quite good in identifying known faces, but those skills are limited when it comes to dealing with a large amount of unknown faces. The computers, with an almost limitless memory and computational speed, should overcome human limitations.

Face recognition finds its application in a wide variety of industry areas such video surveillance, human-machine interaction, photo cameras, virtual reality or law enforcement. Therefore, it's not a problem restricted to computer vision research. Face recognition is a relevant subject in pattern recognition, neural networks, computer graphics, image processing Face recognition is the automatic assignment through which a digital image of a particular person can be analyzed using the features of the face in that image. Face recognition method consists of three components: face detection, feature extraction and face identification.

II. Face Recognition

Face Recognition, as the most successful applications of image analysis and understanding, has recently received significant attention. Recognition implies the tasks of identification or authentication.

Identification involves a one-to-many comparison to fetch unknown identity from a set of known possibilities. Authentication involves a one-to-one comparison to verify a claimed identity. Furthermore, closely related to recognition is classification where the problem is to identify a group of individuals as sharing some common features. Their applications include security monitoring, automated surveillance systems, access control, mug shot identification, suspect versus perpetrator verification, facial reconstruction, victim and missing person identification, design of human computer interfaces, multimedia communication, medical diagnosis and treatment planning.

Fig 1: Configuration of a face recognition system

In a face recognition system, 3 steps includes [1]: Face detection, feature extraction & face recognition. In any system, challenges are race, age, gender, facial expression, or speech may be used in narrowing the search. In order to solve this problem, segmentation of faces (face detection) from cluttered scenes, feature extraction from the face regions, recognition, or verification is used. In identification, the input to the system is an unknown face, and the system reports back the determined identity from a database, whereas in verification problems, the system needs to confirm or reject the claimed identity. The first step in any automatic face recognition systems is the detection of faces in images. After a face has been detected, the task of feature extraction is to obtain features that are fed into a face classification system. Depending on the type of classification system, features can be local features such as lines or facial features such as eyes, nose, and mouth. Face detection may also employ features, in which case features are extracted simultaneously with face detection. Feature extraction is also a key to animation and recognition of facial expressions

III. Methodology used in face detection

The methods used for face detection can be classified in the following categories

A. Knowledge Based Methods

It calculates parameters of human facial feature. Features of a face (like nose, mouth, eyes, lips) and their relationships (like relative distance, intensity) are comparatively simple to take into account. After detection of features, false detection is reduced for verification. This approach is good for face image taken from front and not in different poses.

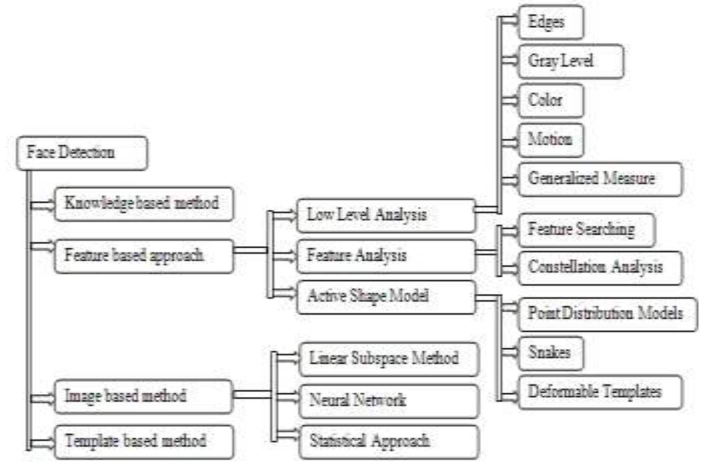

Fig 2: Various face detection approaches

B. Feature-Based Method

Feature-based approach can be further divided into three areas.

1) Low-level Analysis

In low-level analysis visual features are segmented using properties of the pixels. Operators like the Sobel operator, the Mar-Hildreth operator, and a variety of first and second derivatives of Gaussian are used to detect the presence of edge in image. Govindaraju et. al. [2] labeled edges as left side, hairline, and right side, developing a system capable of detecting 76% of faces in a set of 60 images with complex backgrounds, with an average of two false alarms per image. Extraction algorithms can search for local minima to detect darker surrounding and local maxima can indicate bright facial spots such as nose tips.

2) Feature Analysis

There are two approaches. First involves sequential feature searching which is based on the relative positioning of individual facial features. To hypothesized less prominent features, prominent facial features are determined. A facial feature extraction algorithm proposed by Desilva et. al. [3] got 82% accuracy, however Jeng et. al. [4] reported an 86% detection rate. The second technique is constellation analysis, which is less rigid and is more capable of locating faces of various poses in complex backgrounds. Features detected from a multi-scale Gaussian derivative filter using statistical shape theory is capable of detecting 84% of faces. However Probabilistic face models based on multiple face appearance reported 92% detection rate.

3) Active Shape Model

These are three types: snakes, deformable templates and smart snakes. Snakes used to create a head boundary. They lock on to nearby edges, assuming the shape of the head. To achieve it energy function are minimized, which consists of the sum of an internal energy function, defining its natural evolution and an external energy function, which counteracts the internal energy enabling the contours to deviate from the natural evolution. Deformable Templates is an extension to the snake models. Yuille et al [5] used global information of the eye to improve the extraction process. Once established near an eye feature, optimal feature boundaries are minimized using steepest gradient descent minimization. Its Limitations is that they are sensitive to initial placement and the processing time Smart Snakes or Point Distributed Models (PDMs) are compact parameterized descriptions of a shape based upon statistics. They use PCA to construct a linear flexible model from variations of the features in a training set. Face PDM has 95% detection rate.

C. Image-Based Method

Image-based approaches are having three methods: Linear subspace methods, neural networks, and statistical approaches.

1) Linear Subspace Methods

Detection can be represented by methods having statistical analysis, including Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Factor Analysis (FA). In PCA, principal components of faces are found. Each face in the set can then be approximated by combination of the largest Eigenvectors, referred as Eigenfaces. Pentland et. al. [6] proposed a facial feature detector generated from Eigenfeatures, obtained from various templates in a training set. It reported about 94% accuracy. Yang et al [7] proposed a method based on Factor Analysis (FA), which assumes that observed data samples come from a well-defined model. Using a mixture of factor analyzers, training images is used to estimate the parameters in the mixture model. This model is then applied to subwindows in the input image, and the probability of a face being present is returned. Yang et al [7] also proposed a system using LDA which aims for discrimination, where the class of faces and non-faces is divided into subclasses.

2) Neural Networks

Rowley et. al. [8] proposed the first advanced neural approach which reported performance statistics on a large and complex dataset. Their system incorporates face knowledge in the neural network architecture, with specialized window sizes designed to best capture facial information. Images are pre-processed before being classified by the network, the output is post-processed to remove overlapping detections, resulting in one detection per face, and a reduction in false positives. Multiple networks were trained independently and their outputs combined using various arbitration methods to further improve performance.

3) Statistical Approaches

There are some techniques that identify, parameterize and analyze linear subspaces. Other than linear subspaces there are some statistical face recognition techniques which are based on non-linear subspaces (like kernel-PCA and kernel-LDA), transformation (like DCT, DCT & HMM and Fourier Transform) and Support Vector Machine (SVM). Appearance-based approaches for face recognition like PCA, LDA, and probabilistic subspace view a 2D face image as a vector in image space.

$$\frac{P(\text{image} \mid \text{object})}{P(\text{image} \mid \text{non-object})} > \frac{P(\text{non-object})}{P(\text{object})}$$

A face exists at the current location if the above condition is true.

4) Template Matching Method

Template matching is conceptually related to holistic approach which attempts to identify faces using global representations (J. Huang, 1998). These types of methods approach the face image as a whole and try to extract features from the whole face region and then classify the image by applying a pattern classifier. One of the methods used to extract features in a holistic system, is based on statistical approaches which are discussed in the following section.

IV. Methods of Face Recognition

Categorization of face recognition can be made on three methods.

A. Holistic Matching Methods:

In holistic method face recognition is done by taking the whole face as the raw input in the face detection task.

1) Eigenfaces Direct application of PCA

Pentland et. al. [10] proposed that by means of PCA one can transform each original image of the training set into a corresponding Eigenface. An important feature of PCA is that one can reconstruct any original image from the training set by combining the Eigenfaces. Eigenfaces are nothing less than characteristic features of the faces. Therefore original face image can be reconstructed from Eigenfaces, if one adds up all the Eigenfaces (features) in the right proportion.

2) Probabilistic Eigenfaces Two-class Problem with Problem Measure

To avoid drawback of Bayesian method of the need to estimate probability distributions
Moghaddem et. at [12] proposed a much simpler two-class problem from the multiclass problem by using a similarity measure of image differences. Two mutually exclusive classes were defined: ΩI, representing intrapersonal variations between multiple images of the same individual, and ΩE, representing extra personal variations due to differences in identity. Likelihood functions P(Δ|ΩI) and P(Δ|ΩE) were estimated for a given intensity difference, Δ= I1− I2. These likelihood functions and using the MAP rule, two face images are determined to belong to the same individual, if P(Δ|ΩI) and P(Δ|ΩE).

3) Evolution Pursuit Enhanced GA learning-

EP seeks to learn an optimal basis for the dual purpose of data compression and pattern classification. In order to increase the generalization ability of EP, Liu et. al. [13] proposed a balance which minimises the empirical risk encountered during training and narrowing the confidence interval for reducing the guaranteed risk during future testing on unseen data. Toward that end, EP implements strategies characteristic of genetic algorithms (GAs) for searching the space of possible solutions to determine the optimal basis. EP starts by projecting the original data into a lower-dimensional whitened PCA space.

4) ICA-based Feature Analysis

Bartlett et. al. [14] proposed that a independent-component analysis which is a generalization of PCA, which décor relates the high-order moments of the input in addition to the second-order moments. Two architectures have been proposed for face recognition the first is used to find a set of statistically independent source images that can be viewed as independent image features for a given set of training images and the second is used to find image filters that produce statistically independent outputs.

5) PDBNN Probabilistic Decision Based NN –

Lin et al. [15] proposed system which is based on a probabilistic decision-based neural network. It consists of three modules: a face detector, an eye localizer, and a face recognizer. To improve robustness, the segmented facial region images are first processed to produce two features at a reduced resolution of 14×10: normalized intensity features and edge features, both in the range [0, 1]. These features are fed into two PDBNNs and the final recognition result is the fusion of the outputs of these two PDBNNs.

B. Feature-based (Structural) Matching Methods-

In these methods, local features such as the eyes, nose, and mouth are first extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier.

A. Dynamic Link Architecture Graph matching methods -
Okada et al. [16] proposed system in which DLAs attempt to solve some of the conceptual problems of conventional artificial neural networks, the most prominent of these being the representation of syntactical relationships in neural networks. DLAs use synaptic plasticity and are able to form sets of neurons grouped into structured graphs while maintaining the advantages of neural systems.

B. Hidden Markov Model, HMM Methods

The first efforts to use Hidden Markov Model (HMM) were introduced by Samaira and Young. HMM has been worked effectively for images with variations in brighting, facial expression, and orientation. Thus, it has an advantage over the appearance based approaches. For processing images using HMM, the temporal or space sequences has been considered. HMM has been defined as a set of finite states with associated probability distributions. The reason why it is named Hidden Markov Model is that the states are not visible and only the result is visible to the external user. . It is constructed of a number of states that can be observed and probabilistic transitions. The probability of the transition from the current state to the next one depends solely on the state the model is in the current time step.

C. Hybrid Methods

This method is best among above two methods. It uses both local features and the whole face region to recognize a face.

1) Modular Eigenface Modules

One can take two approaches to handling images from multiple views, as given by Pentland et.al. [18]. The first approach constructs a set of Eigenfaces that represent all the images from all the views. The other better approach known as view-based Eigenspaces, uses separate Eigenspaces for different views, so that the collection of images taken from each view has its own Eigenspace.

2) Hybrid LFA (Local feature Analysis)-

LFA is used to extract topographic local features from the global PCA modes, by Penev et.al. [19]. Unlike PCA, LFA kernels $K(\mathbf{x}i, \mathbf{y}\mathrm{i})$ has selected grids $\mathbf{x}i$ have local support. The search for the best topographic set of sparsely distributed grids $\{xo\}$ based on reconstruction error is called sparsification. Two interesting points are demonstrated: (1) using the same number of kernels, the perceptual reconstruction quality of LFA based on the optimal set of grids is better than that of PCA. (2) keeping the second PCA Eigenmodel in LFA reconstruction reduces the mean square error.

3) Component-based Face Region and Components

The basic idea of component-based methods is to decompose a face into a set of facial components that are interconnected by a flexible geometrical model. Changes in head pose mainly lead to changes in the positions of facial components which could be accounted for by the flexibility of the geometric model as proposed by Heisele et. al. [20]. Drawback of the system is that it needs a large number of training images taken from different viewpoints.

V. Different Statistical Approaches for Recognition Algorithm

A. Architecture of Neural Network

The neural network needs 960 inputs and 94 neurons in its output layer to identify the faces. The network is a two-layer log-sigmoid/log-sigmoid network [6-8]. The log-sigmoid transfer function was picked because its output range (0 to 1) is perfect for learning to output Boolean values (see figure1) [5]. The hidden layer has 200 neurons [5]. This number was picked by guesswork and experience [5]. If the network has trouble learning, then neurons can be added to this layer [5, 9]. The network is trained to output a 1 in the correct position of the output vector and to fill the rest of the output vector with 0's. However, noisy input images may result in the network not creating perfect 1's and 0's. After the network has been trained the output will be passed through the competitive transfer function. This function makes sure that the output corresponding to the face most like the noisy input image takes on a value of 1 and all others have a value of 0. The result of this post-processing is the output that is actually used [9].

Training: To create a neural network that can handle noisy input images it is best to train the network on both ideal and noisy images. To do this the network will first be trained on ideal images until it has a low sum-squared error. Then the network will be trained on 10 sets of ideal and noisy images. The network is trained on two copies of the noise-free database at the same time as it is trained on noisy images. The two copies of the noise-free database are used to maintain the network's ability to classify ideal input images. Unfortunately, after the training described above the network may have learned to classify some difficult noisy images at the expense of properly classifying a noise free image. Therefore, the network will again be trained on just ideal images. This ensures that the network will respond perfectly when presented with an ideal face. All training is done using back propagation with both adaptive learning rate and momentum.

B. Component-based Face Detection

In this approach, two support vector machine classifiers are used. The first classifier detects the components of the current image window as a potential face and the second classifier checks the geometry of these components to match that of a face or not. In this, a component based approach is more robust to occlusion than approaches that depends on the whole face.

C. Real Time 2-D Face Detection Using Color Ratios and K Mean Clustering

An algorithm for detecting faces in real time MPEG videos was presented after converting the MPEG stream into JPEG file sequences. The application turns into still image face detection problem where two phases are used for the detection purpose. The first is the Skin region detection classifier. Images passed to this classifier are searched for skin regions, images that don't contain skin regions are discarded, and images with skin regions are passed to a K-Mean face segmentation clustering unit for further investigation of the skin regions to match a human face. (Byrd and Balaji, 2006). Using skin color to detect human faces was a studied by many researchers where they presented a stochastic model for the human skin color and applied a real time face tracker system with motion compensation and motion model to predict the search window. The main problem with using skin color models as a main method for face detection is that it returns false detects also for other parts of the body but its high performance makes it desirable to use as a candidate selection method and use a more robust method later for an accurate decision. Jones and Rehg (2002) built a skin and non-skin classes color model and applied it on detecting naked people in still images.

D. Float Boost Learning and Statistical Face Detection

This method works to improve the Ada Boost method to achieve a minimal error rate and requires less weak classifiers to achieve a lower error rate than that of the Ada Boost. Ada Boost learns a sequence of weak classifiers which when combined form a strong classifier of a higher accuracy. Viola-Jones work which primarily focused on frontal faces views, and their work was derived from Ada Boost learning algorithm, mainly consisted of three stages. The first is to identify a minimal set of features out of huge number of features, the second stage is learning weak classifiers to identify each of these features and the third one is the combination of these weak classifiers into a strong classifier. This hierarchy leads to one of the best frontal real time faces detection systems, the Float Boost method which deals with multi-view faces where it is estimated that 75% of real face images are non-frontal. The system applies the Float Boost algorithm for learning the weak classifiers and then forms them into a pyramid to make the final strong classifier. It runs at 200ms for a 320x240 image on a 700MHz Pentium III processor, (Li and Zang,2004).

E. View-based Methods for Face Detection

Feature based methods that depend on the prior knowledge of the face geometry or the relative distribution of facial features becomes more troublesome as the background scenery gets more complicated and allow for more errors due to modelling inaccuracy or the possible lack of coded knowledge of the face. This is why view-based methods were introduced in an attempt to detect the human face without depending on the knowledge of its geometry. View-based methods treats the face detection problem as a pattern recognition problem by having two separate classes, faces and none faces, and by implicitly extracting the knowledge embedded in the face to create a proper boundary between face and non-face samples in the image-two dimensional pixels space.

This approach requires training to produce the final classifier which will be applied at all positions at all scales, where windows are extracted, possibly re sampled (re-scaled). This exhaustive search can be boosted by increasing the scan and/or scaling steps to reduce the total number of scanned windows. Algorithms used in the view-based approach include PCA (Principal Component Analysis), Neural Networks, SVM Support Vector Machines and other statistical methods that can learn from examples (Lin Haung 2004). In the subsequent sections several algorithms will be overviewed that belong to the both categories formerly mentioned.

F. Face Detection using a Boosted Cascade of Simple Features

An approach used to detect objects in general is applicable to human faces as well. This method proved to detect objects extremely rapidly and is comparable to the best real time face detection systems, Viola and Jones (2004) presented in their research a new image representation called Integral Image which allows fast calculation of image features to be used by their detection algorithm. The second step is an algorithm based on Ada Boost which is trained against the relevant object class to select a minimal set of features to represent the object. The third step is introducing series of classifiers which have an increasing complexity, these set of cascade classifiers allows to rapid discard of most non-objects at early stages, allowing more time to be spent on the final stages to yield higher detection rates and thus boosting both accuracy and processing time for the object detection task. Viola and Jones presented a frame work for object detection motivated by faced detection and yielded some good results as viewed by their research for real time face detection at high rates.

G. Classification based Face Detection using Gabor Filter Features

Lin-Lin hung in 2004 proposed a paper in which they designed four filters for extracting features from the local image. The feature vector based on the Gabor filters is used as the input of the classifier, which is a polynomial neural network (PNN) on a reduced subspace learned by PCA. In classification based methods, face detection is commonly done by shifting a search window over an input image and by categorizing the object with a classifier. The Gabor representation of an image is the convolution of the image with the Gabor filters, based on the Gabor representations, a feature vector is formed. The Eigenvectors corresponding to the m largest Eigen values are selected such that the error of pattern reconstruction from the subspace is minimized and we integrate distance from feature subspace (DFFS) into PNN. 2987 images were used to extract face samples, which contained 2900 real faces. The local image within the box is stretched and compressed to give four samples. In addition the mirror images of the above five samples are also included. In total 29,900 samples were collected. The non-face samples were collected in three phases. In first, the local image of search windows in background area are compared with the mean vector if face samples and a threshold is considered as a confusing non-face sample. 38,834 non-face samples were gathered. In the second and third phase, the local window images are classified by the PNN, trained with the previously collected samples and the local image which does not contain a face but have an output value higher than the threshold is considered as a confusing non-face sample. About 60,000 non-face samples were collected and finally PNN was retrained with the face and non-face samples collected.

Experiments show that detection performance is good with fewer false positives and consumes less computation resources.

H. Neural Network-Based Face Detection:

Many view based approaches to detect faces in still images were introduced and proved that face detection problem can be effectively solved by using Neural Network. The main problems addressed in using machine learning techniques to learn detecting faces was that faces in images varied considerably with different lighting conditions, pose, occlusion and facial expressions. Compensating for these variations was important for the learning process and it was essential to choose a representative set of non faces where training set size could increase indefinitely. So the training used a bootstrap method (Davor, Ivan 2007) to actively add training samples as the training progress, and emphasize those samples which were not classified correctly. The training set of faces were aligned by manually labelling few features in each face image. After labelling the face training set, a transformation was calculated which included any transition, rotation and scale which minimized the sum of square distance between each pair of the training set. The initial aligning step was to calculate the parameters necessary to make this transformation possible. After this each of the training set was aligned using this transformation, after the face set was properly aligned they were passed to a pre-processing stage which counted for the source of variation caused by camera and lighting conditions where poorly lit faces and faint contrast were compensated. The pre-processing used in Rowley research was basically subtracting a linear function which was calculated by computing the average brightness in the current face window from the other reprocessing function that has a histogram equalization which is a nonlinear function that emphasize the intensities in the chosen window. Rowley also presented some ideas about using intelligent methods for compensating the lighting conditions in the face images like using neural networks for compensation however applying this could lead to increase the false detections since pre-processing will also be applied at test sets which could make non face images look more like a face after the lighting compensation which was learned to compensate face images only.

I. Bio-inspired Ada boost Method for Efficient Face Recognition:

A research was presented by Suman Sedai and Phill Kyu in 2007 based on the Ada Boost algorithm and bio- inspired evolutionary search in which after extracting the feature vector of the face image based on fixed fiducial points. They decomposed the strong feature into several feature subsets using GA and classification models of each feature subsets are combined using the Ada Boost algorithm. GA searches the best feature combination that gives minimum training error. The outcome of experiments suggested that the classification model using aggregation of feature combinations by means of Ada Boost and GA gave better result than classification model that used the entire feature vector. Here a genetic algorithm is used to decompose the large set of feature into small subset and Ada Boost algorithm to combine the result of feature subset. In this decomposition, each result is a weak learner for the Ada Boost algorithm. It is an adaptive algorithm to boost sequence of classifiers, in that the weights are updated dynamically according to the errors in previous learning. Landmark points of each image are manually labelled at 32 feature points and Gabor feature vector at the each point is extracted to form feature vector for a facial image. Input to the Ada Boost is constructed by creating two pair combination feature vector of different images. The highest recognition rate of 96.4% occurs at d=16, optimal feature combination occurs at d=16. The recognition success and corresponding error rate at equal error point is different for different feature combination schemes.

J. Face Recognition Using Multiscale Gabor Wavelet

A research that proposed and analyzed multiscale Gabor Wavelet and Eigenface method for face recognition was presented by Lin Haung in 2007. The face images are processed by using one-dimensional (1-D) filter masks to extract the Gabor features without two-dimensional (2-D) Fourier transform. In this paper, multiscale Pyramidal Gabor Wavelet Eigenface (PGE) is applied to face recognition. The results of analysis and experiments show that it can achieve even faster computational speed and use less computer memory than the classic 2-D Gabor wavelet based schemes. Meanwhile, it overcomes weak facial feature representation of the Eigenface method, due to its sensitivity to input image deformations caused by expression, lighting and pose variations.

The feasibility and performance of the proposed algorithm was verified by the standard AT&T database, which contained 400 images of 40 subjects with variation in poses, expression, different viewing direction etc. And each subject had 10 face images taken. The training set was constructed by selecting 5 images for each subject, and testing set was the relative rest of the database. No overlap existed between the training and testing sets. The recognition rates of Eigenface procedure was lower than that of PGE algorithm. It was shown that the best performances of 97.0%, 95.0%, and 87.5% recognition rates were achieved by PGE algorithm, 2-D Gabor wavelet method and stand-alone Eigenface method, respectively.

VI. CONCLUSION

This paper has discussed various face detection and feature extraction techniques. Feature extraction is an important part of face recognition because without having an input we cannot drive an output so face extraction is the first base of this paper. This paper discusses various feature extraction technique. Every technique has its pros and cons such as we can see that high computational cost is sometimes very high and speed is good, illumination problem, pose variation etc.

This work has presented a survey about face recognition. These are the current lines of research:

1. We have demonstrated how a face recognition system can be designed by artificial neural network. Note that the training process did not consist of a single call to a training function. Instead, the network was trained several times on various input ideal and noisy images of faces. In this case training a network on different sets of noisy images forced the network to learn how to deal with noise, a common problem in the real world.

2. Here a genetic algorithm is used to decompose the large set of feature into small subset and Ada Boost algorithm to combine the result of feature subset. In this decomposition, each result is a weak learner for the Ada Boost algorithm.

3. Color ratios and Kmean clustering The main problem with using skin color models as a main method for face detection is that it returns false detects also for other parts of the body but its high performance makes it desirable to use as a candidate selection method and use a more robust method later for an accurate decision. Jones and Rehg (2002) built a skin and non-skin classes color model and applied it on detecting naked people in still images

There are a number of directions for future work. We will discuss about Gabor filters and Wavelet that will work on a large number of images and it will produce the better performance in terms of detection and false positive rates

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