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FACE RECOGNITION APPROACHES: A SURVEY

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Abstract-Face recognition has been the most widely used application of image analysis. Its popularity is due to wide range of commercial and law enforcement applications and presence of latest techniques. It also has several applications in areas such as content-based image retrieval, video coding, video conferencing, crowd surveillance, and intelligent human–computer interfaces. But current systems are having laggings, which still needed to be worked upon like illumination and pose variations.

This paper is a study of various techniques being used for face recognition. A face recognition system includes three steps face detection, feature extraction and face recognition. This paper includes various recognition techniques and descriptions of representative methods. 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.

Keyword: - Challenges, face detection, face recognition, PCA, HMM, LDA.

1. Introduction

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.

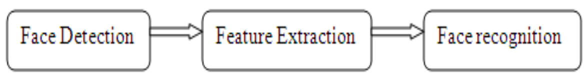

Fig 1- Configuration of a face recognition system [1]

In a face recognition system, 3 steps includes: 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.

2. Face Detection Strategies

Face detection can be represented by

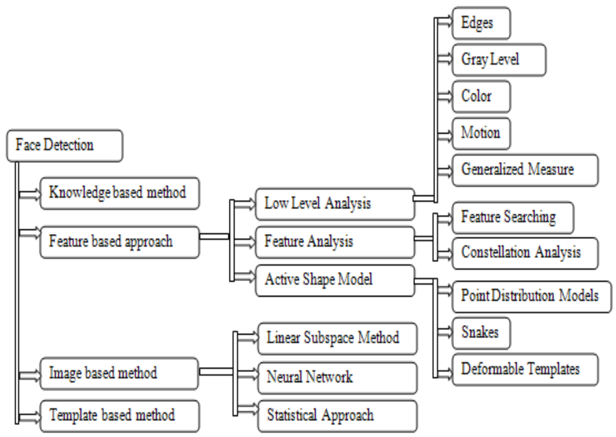

Fig 2 Various Face detection approaches

Face detection techniques and algorithm deals with detection of face in clutter background with poses. True positives (detection rate) and false positives (detections of non face regions) would have to be very high and very low respectively for an ideal system.

2.1 Knowledge Based Method-

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.

2.2 Feature-Based Method-

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

2.2.1 Low-level Analysis-

In low-level analysis visual features are segmented using properties of the pixels. Operators like the Sobel operator, the Marr-Hildreth operator, and a variety of first and second derivatives of Gaussians 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.

2.2.2 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 De silva 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.

2.2.3 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.

2.3 Image-Based Method-

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

2.3.1 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.

2.3.2 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.

2.3.3 Statistical Approaches-

Statistical approach includes based on information theory, support vector machines and Bayes' Decision Rule. Huang et. al. [9] developed a system based on Kullback relative information. This divergence is a non-negative measure of the difference between two probability density functions. During training, for each pair of pixels in the training set, a joint-histogram is used to create probability functions for the classes of faces and non-faces using a large quantity of 11x11 pixel images and results in a set of look-up tables of likelihood ratios. Poor detection are completely removed from the look-up tables to reduce computational requirements. The system was further improved by incorporating a bootstrap training algorithm.

A SVM with a 2^{nd} degree polynomial as a kernel function is trained with a decomposition algorithm. Images are pre processed and trained with a bootstrap learning algorithm. Schneiderman et. al. [10] proposes two face detectors based on Bayes' decision rule.

$$\frac{P(\text{image} \mid \text{object})}{P(\text{image} \mid \text{non-object})} > \frac{P(\text{non-object})}{P(\text{object})} \quad \text{-----(1)}$$

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

2.4 Template Matching Method-

Template matching methods use the correlation between pattern in the input image and stored standard patterns of a whole face / face features to determine the presence of a face or face features. Predefined templates as well as deformable templates can be used.

3. Face Recognition Approach

Categorization of face recognition can be made on three methods.

3.1 Holistic matching methods-

These methods use the whole face region as the raw input to a recognition system. One of the most widely used representations of the face region is eigenpictures, which are based on principal component analysis.

3.1.1 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.

3.1.2 Probabilistic eigenfaces Two-class problem with prob. 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: Ω_I, representing intrapersonal variations between multiple images of the same individual, and Ω_E, representing extrapersonal variations due to differences in identity. Likelihood functions $P(\Delta|\Omega_I)$ and $P(\Delta|\Omega_E)$ were estimated for a given intensity difference, $\Delta= I_1 - I_2$. These likelihood functions and using the MAP rule, two face images are determined to belong to the same individual, if $P(\Delta|\Omega_I)$ and $P(\Delta|\Omega_E)$.

3.1.3 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.

3.1.4 ICA-based feature analysis-

Bartlett et. al. [14] proposed that a independent-component analysis which is a generalization of PCA, which decorrelates 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.

3.1.5 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.

3.2 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.

3.2.1 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.

3.2.2 Hidden Markov model, HMM methods-

Nefian et. al. [17] proposed system in which HMMs are based on the well-known Markov chains that are often used in probability theory. The Markov chain is a probabilistic signal generator with a single state memory. 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.

3.3 Hybrid methods-

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

3.3.1 Modular eigenfaces, Eigenfaces and eigenmodules-

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.

3.3.2 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.

3.3.3 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.

4. CONCLUSION

After study of various methods and steps of a face recognition system, it is concluded that image-based approaches is best among others because face images belong to face class. Geometric changes can be overcome by local appearance based approaches, 3D enhanced approaches, and hybrid approaches. By holistic matching methods, accurate location of key facial features such as eyes is obtained to normalize the detected face. Also it is concluded that, when the number of training samples per class is large, LDA is the better than PCA.

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