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FACE RECOGNITION TECHNIQUES: CLASSIFICATION AND COMPARISONS

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ABSTRACT: Human brains can remember and recognize a vast array of faces, getting a computer to do the same is difficult but in modern world there would be many uses of such systems. Face reorganization has been a fast growing, challenging and interesting area in real time application. It can be widely use for image and film processing; this requires computational models for the identification of the face. This model should be easy and simple when implemented. In this paper we will review the different methods for face recognition, their advantages and disadvantages.

Keywords: PCA, LDA, Neural Networks, BPN and RBF

1. INTRODUCTION

Face recognition is a biometric technique used for surveillance purposes such as search for wanted criminals, suspected terrorists, and missing children. The term face recognition refers to identifying, by computational algorithms, an unknown face image. This operation can be done by comparing the unknown face with the faces stored in database. Face recognition has three stages *a*) face location detection *b*) feature extraction *c*) facial image classification. Various face recognition algorithm exits and each has advantages and limitation. Lots of research work has been published on face recognition. Eigenfaces method proposed by Turk and Pentland in [1] uses a nearest neighbour classifier while feature-line-based methods explained by Li and Lu in [2], replace the point-to-point distance with the distance between a point and the feature line linking two stored sample points. In Fisherfaces method [3] authors uses linear/Fisher discriminant analysis (LDA /FLD). Bayesian methods proposed by Moghaddam and Pentland [4] use a probabilistic distance metric while SVM method uses a support vector machine as the classifier [5]. Earlier methods belong to the category of structural matching methods, using the width of the head, the distances between the eyes and from the eyes to the mouth, etc., or the distances and angles between eye corners, mouth extrema, nostrils, and chin top [6]. More recently, a mixture-distance based approach using manually extracted distances was reported in [7] by Cox et al.

2. PCA (PRINCIPAL COMPONENT ANALYSIS)

Principal component analysis is a variable reduction procedure. It is useful when you have obtained data on a number of variables (possibly a large number of variables), believe that there is some redundancy in those variables. In this case, redundancy means that some of the variables are correlated with one another, possibly because they are measuring the same construct. Because of this redundancy, you believe that it should be possible to reduce the observed variables into a smaller number of principal components (artificial variables) that will account for most of the variance in the observed variables. The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called 'Eigenfaces', which are actually the principal components of the initial training set of face images. An important feature of PCA is that one can reconstruct any original image from the training set by combining the Eigenfaces. The technique used in creating Eigenfaces and using them for recognition is also used outside of facial recognition. This technique is also used for handwriting analysis, lip reading, voice recognition, sign language/hand gestures interpretation and medical imaging analysis.

2.1 Advantages of PCA

i. Recognition is simple and efficient compared to other matching approaches.

ii. Data compression is achieved by the low-dimensional subspace representation.

iii. Raw intensity data are used directly for learning and recognition without any significant low-level or mid-level processing low-level or mid-level processing.

iv. No knowledge of geometry and reflectance of faces is required

2.2 Disadvantages of PCA

i. The method is very sensitive to scale, therefore, a low-level preprocessing is still necessary for scale normalization.

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ii. Since the Eigenface representation is, in a least-squared sense, faithful to the original images, its recognition rate decreases for recognition under varying pose and illumination.

iii. Though the Eigenface approach is shown to be robust when dealing with expression and glasses, these experiments were made only with frontal views. The problem can be far more difficult when there exists extreme change in pose as well as in expression and disguise.

iv. Due to its "appearance-based" nature. First, learning is very time-consuming, which makes it difficult to update the face database.

3. LDA (LINEAR DISCRIMINANT ANALYSIS)

Linear Discriminant Analysis is a well-known scheme for feature extraction and dimension reduction. It has been used widely in many applications such as face recognition, image retrieval, microarray data classification, etc. Classical LDA projects the data onto a lower-dimensional vector space such that the ratio of the between-class distances to the within-class distance is maximized, thus achieving maximum discrimination. The optimal projection (transformation) can be readily computed by applying the Eigen decomposition on the scatter matrices Linear discriminant analysis (LDA) and the related Fisher's linear discriminant are methods used in statistics, pattern recognition and machine learning to find a linear combination of features which characterize or separate two or more classes of objects or events [8-9]. The resulting combination may be used as a linear classifier or more commonly, for dimensionality reduction before later classification.

3.1 Advantages of LDA

i. The Fisherface projection approach is aimed to solve the illumination problem by maximizing the ratio of between-class scatter to within-class scatter; however, finding an optimum way of projection that is able to simultaneously separate multiple face classes is almost impossible.

ii. LDA based algorithms outperform PCA based ones, since the former optimizes the low dimensional representation of the objects with focus on the most discriminant feature extraction while the latter achieves simply object reconstruction.

3.2 Disadvantages of LDA

i. An intrinsic limitation of classical LDA is the so-called singularity problem, that is, it fails when all scatter matrices are singular.

ii. However, a critical issue using LDA, particularly in face recognition area, is the Small Sample Size (SSS) Problem. This problem is encountered in practice since there are often a large number of pixels available, but the total number of training samples is less than the dimension of the feature space. This implies that all scatter matrices are singular and thus the traditional LDA algorithm fails to use.

4. COMPARISON OF PCA AND LDA

There has been a tendency in the computer vision community to prefer LDA over PCA. This is mainly because LDA deals directly with discrimination between classes while PCA does not pay attention to the underlying class structure. When the training set is small, PCA can outperform LDA. When the number of samples is large and representative for each class, LDA outperforms PCA. Many works analyzed the differences between these two techniques, but no work investigated the possibility of fusing them. In our opinion, the apparent strong correlation of LDA and PCA, especially when frontal views are used and PCA is applied before LDA, discouraged the fusion of such algorithms. However, it should be noted that LDA and PCA are not as correlated as one can think, as the LDA transformation applied to the principal components can generate a feature space significantly different from the PCA one. Therefore, the fusion of LDA and PCA for face recognition and verification is worth of theoretical and experimental investigation.

5. NEURAL NETWORKS APPROACH

A successful face recognition methodology depends heavily on the particular choice of the features used by the pattern classifier Neural based Face recognition is robust and has better performance of more than 90% acceptance ratio. Back propagation is a multi-layer feed forward, supervised learning network based on gradient .The Back Propagation Network (BPN) is the best known and widely used learning algorithm in training multilayer perceptrons (MLP). The MLP refer to the network consisting of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer of computation nodes. The input signal propagates through the network in a forward direction, from left to right and on a layer-by-layer basis. Artificial neural networks are algorithms that can be used to perform nonlinear statistical modeling and provide a new alternative to logistic regression, the most commonly used method for developing predictive models for dichotomous outcomes in medicine [10-11]. Neural networks offer a number of advantages, including requiring less formal statistical training, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, and the availability of multiple training algorithms. Disadvantages include its "black box" nature, greater computational burden, proneness to over fitting, and the empirical nature of model development.

5.1 Advantages of BPN

i. This BPNN provides a computationally efficient method for changing the weights in feed forward network, with differentiable activation function units, to learn a training set of input-output data.

ii. Being a gradient descent method it minimizes the total squared error of the output computed by the net.

iii. When BPNN technique is combined with PCA, non linear face images can be recognized easily, this shows that this method has the acceptance ratio is more than 90 % and execution time of only few seconds.

5.2 Disadvantages of BPN

i. It is a slow technique.

In case of RBF, Consists of 3 layers (input, hidden, output) Input layer made up of nodes that connect network to environment. At input of each neuron (hidden layer), distance between neuron center & input vector is calculated. Apply RBF (Gaussian bell function) to form output of the neurons. Output layer is linear and supplies response of network to activation function. A radial basis function network is an artificial neural network, which uses radial functions as activation functions. A radial basis function (RBF) is a real- valued function whose value depends only on the distance from the origin. RBF networks are claimed to be more accurate than those based on Back- Propagation (BP), and they provide a guaranteed, globally optimal solution via simple, linear optimization .One advantage of radial basis networks over back propagation is that, if the input signal is non-stationary, the localized nature of the hidden layer response makes the networks less susceptible to phase include the learn rate and tolerance for errors. RBF trains faster than a MLP. Another advantage that is claimed is that the hidden layer is easier to interpret than the hidden layer in an MLP. RBF is quick to train.

6. CONCLUSION

Face recognition consist many different techniques to recognize a face. We have gone through PCA and LDA, PCA is the simplest, efficient and oldest one but learning is time consuming so we prefer LDA. In LDA the singularity problem comes however it best tries to sort the illumination problem. In order to improve the recognition we apply neural networks which increases the recognition time but improves the efficiency. Further there are different learning's like Back propagation, radial basis function etc. The BPNN is not only efficient but also non linear faces can also be recognized. BPNN was slow so we switch towards RBF which is more accurate, quick and easy. The QMW Vision Group, who have been making rapid progress in real time face tracking and localization. Significant recent work has allowed more robust segmentation through color detection, and confidence levels can now be provided with each segmented frame to denote the likelihood of a face being present in the image.

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