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HUMAN FACE AND EXPRESSION RECOGNITION WITH KERNEL FISHER ANALYSIS

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Abstract— Human Face recognition is a exigent task in computer vision and pattern detection Face recognition is thorny because it is a real world problem. The Human Face is multifarious, natural object that tends not to have easily acknowledged features and edges. Because of this, it is decisive to develop a mathematical model of that face that can be used as prior knowledge when analyzing a particular image. Kernel fisher Analysis (KFA) method is used to improve the performance of the face reorganization systems. There are other methods PCA, KPCA, KCA, and LDA which also used to improve the performance of the face recognition system. So in this paper we are going to review the different methods and techniques used to for the face and emotion identification.

Index Terms— Face Detection, Facial Expression Recognition, Linear Discriminate Analysis (LDA), Kernel Fisher Analysis (KFA), Kernel Principal Component Analysis (KPCA), Principal Component Analysis (PCA).

I. INTRODUCTION

In face recognition technique image normalization and processing are the one of the significant parts. Variations in lighting circumstances produce radically decrease of recognition performance. If an input image has dark lighting places and low contrast, its brightness and contrast should be enhanced. The histogram equalization used commonly cannot correctly recover all region of the image. When some places on the resulted image will remain too bright or too dark and the face image has irregularly lighted conditions. Face image has digital depiction as any digital image; this mean has a binary illustration of a two-dimensional image. The digital illustration is an array of two dimensions called pixels. Each pixel has a arithmetical value which in monochromatic images appears as a grey level [1].

In last few decades, different face recognition methods and techniques have been reviewed and proposed in [2] [3] [4] [5].

Feature extraction is the most important part of the face recognition system or technique. In the current scenario an appropriate face representation system is required to analyze. This must be powerful and also computationally functional to possible extrinsic and intrinsic facial variations. There are different feature extractions methods are proposed for the face recognition system and some of the important methods are

Principal Component Analysis (PCA) [2] [6], Linear Discriminant Analysis (LDA) [7], kernel methods [8],

Eigenfaces [2], Laplacian faces [9], Fisherfaces [10], elastic bunch graph matching [11], neural networks [12] and support vector machine [13].

In the literature of the face recognition, there are different face representation methods based on global features, including a big number of spatial-frequency techniques and some subspace-based methods [1]. In face reorganization technique large databases of face images are used to identify the individual person. The strength of each pixel in a face image is entered as input trait, in conventional appearance-based systems. As there are many thousands of pixels in a face image [14], facial image data are always high-dimensional and substantial computational time is obligatory for the successful classification purpose. Thus projecting objects to a lower dimensional space entity are commonly used by subspace methods. In practical cases, one is often forced to use linear techniques when the image dimension is very outsized. LDA and PCA are the two important liner techniques used for extracting characteristics of the facial image. Most of the researchers mainly focused on projective transforms. Generating feature vector for each face image is the one of the essential part of these methods is then categorize the input face image in large database by the feature selection methods. Generating feature vector also has the utility of curtailing dimension of the input images [4]. Principal component analysis (PCA) method accomplish the dimension reduction by providing the real face image data onto lower dimensional subspace crossed by the best eigenvectors of the covariance matrix. Linear Discriminant Analysis (LDA) searches for the capitalize on between class scatter, while constraining the data points of the same class to be as near to each other as possible, this mean penetrating for the minimizing within class scatter because LDA method looks for the projective axes on which the data points of two or more dissimilar classes are distant from each other [7]. Kernel PCA and kernel fisher analysis are nonlinear form of PCA and LDA respectively. Numerous researchers proposed techniques based on spatial-frequency methods, such as Discrete Cosine Transform (DCT) and Fourier transform [12] [14] [15]. In these methods, face images are planned to an inferior frequency domain bands that have the most facial discerning features and throwing away high bands that having noise [14].

The augmentation of face image is an central aspect in civilizing the performance of face recognition system. The foremost purpose of the face image enhancement is that the resulted images have better visual eminence than the input one. Face image can be enhanced, by enhancing the brightness, contrast and resolution of image. This is a part of pre-processing stage that can influence the feature extraction and finally recognition feat. For instance in [16], the image enhancement has been measured in face recognition technique. Song et al. [17], analyze prior to feature extraction segmentation, the exemplify dissimilarity between right and left part of face from the input image. If there is a drudgery amount of difference than take the mirror of average illuminated part.

The endeavor of this work is to study the outcome of image pre-processing on escalating the face recognition pace and to study the impact of these procedures on the image recognition system.

The organization of the paper is as follows section 1 gives the brief introduction to the Face Recognition. In section 2 different feature extraction algorithms used for face recognition are studied. In section 3 different face recognition techniques are studied. Section 4 gives the conclusion followed by references.

II. Related Work

Over the last decade, there has been a great pact of interest in the use of framework to help improve face recognition accuracy in personal photos. A topical survey of context-aided face recognition can be found in [18]. Zhang et al. (Zhang et al. 2003) occupied body and clothing in addition to face for people recognition. Davis et al. [19] developed a context-aware face recognition system that develops GPS-tags, time-stamps, and other metadata. Song and Leung [17] proposed an adaptive format to combine face and clothing features based on the time-stamps. These methods indulgence various forms of relative cues as linearly additive features, and thus generalize the interaction between different domains.

Assortments of methods based on co-occurrence have also been proposed. Naaman et al. [20] leveraged time-stamps and GPS-tags to diminish the candidate list based on people co-occurrence and temporal/spatial re-occurrence. Gallagher and Chen [18] projected an MRF to encode both face similarity and distinctiveness. In later work by the same authors [18], a group aforementioned is added to capture the tendency that certain groups of people are more likely to appear in the same photo.

In addition, Anguelov et al. [21] automated an MRF model to integrate face similarity, clothing similarity and exclusivity. There is also a lot of research on use of framework in object recognition and scene classification. For example, Torralba et al. [22] used scene context as a prior for object detection and recognition. Rabinovich et al. [23] anticipated a CRF replica that utilizes object co-occurrence to help object categorization. Galleguillos et al. [24] extended this framework to use both object co-occurrence and spatial patterns for image segmentation and gloss.

II. ALGORITHMS

A. Principal Component Analysis (PCA):

The Principal Component Analysis (PCA) is exceedingly used in face recognition, is an influential algorithm based feature extraction technique, which pertains the Karhunen-Loéve transform to a set of training images and gain a number of projection axes that proceed as the source vector for the PCA subspace. All images of discern faces are projected against the face space to locate set of weights that portray the input of each vector. For categorize an unknown person, his normalized image is first anticipated onto face space to achieve its set of weights. Than we evaluate these weights to sets of weights of known people from the data bases. If we deem the image elements are the random variables, the PCA basis vectors are defined as eigenvectors of scatter matrix S_T:

$$S_T = \sum_{i=0}^{m}(x_i - \mu).(x_i - \mu)^T \qquad (1)$$

Where μ is the mean of all images in the training set. x_i is the i-th image with its columns concatenated in a vector and *M* is the number of all training images. The projection matrix W_{PCA} is composed of *m* eigenvectors corresponding to *m* eigenvalues of scatter matrix S_T , thus creating an *m* dimensional face space. Since these eigenvectors (PCA basis vectors) look like some ghostly faces they were conveniently named eigenfaces.

B. Linear Discriminate Analysis (LDA)

Unlike the principal components analysis PCA, which considers only the variance of the training images to construct a subspace; linear discriminate analysis (LDA) aims at improving upon PCA by also taking the class-membership information of the training images into account when seeking for a subspace. So, the LDA method expose the vectors in the essential space that best discriminate among classes. For all samples of all classes it defined two matrixes: between-class scatter matrix S_B and the within-class scatter matrix S_w . S_B .Represents the scatter of features around the largely mean μ for all face classes and S_w represents the scatter of features around the mean of each face class:

$$S_B = \sum_{i=0}^{c} M_i.(\mu_i - \mu).(\mu_i - \mu)^T \qquad (2)$$

$$S_w = \sum_{i=1}^{c} \sum_{x_k \in X_i}^{n} (x_k - \mu_i).(x_k - \mu_i)^T \quad (3)$$

C. Kernel principal component analysis (KPCA)

KPCA main technique is calculating PCA conversion in a mapping space by a Non-linear mapping function which for estimating this mapping, kernel idea is used. Consider $\emptyset(x_1), \ldots \ldots \emptyset(x_N)$are mapped data which their mean is not zero. First mapped data mean becomes zero following formula10:

$$\hat{\varphi}(X_k) = \varphi(X_k) - \frac{1}{N}\sum_{j=1}^{n} \varphi(X_j) \quad (4)$$

Covariance matrix is calculated by formula:

$$\textstyle\sum_{\wedge} = \frac{1}{N}\sum_{j=1}^{n} \hat{\varphi}(X_j)\hat{\varphi}(X_j)^T \quad (5)$$

D. Kernel fisher analysis (KFA)

The main idea of this method is to yield a nonlinear discriminate analysis in the higher space. The input data is projected into an implicit feature space by nonlinear mapping, $\varphi: x \in R^N \rightarrow f \in F$ then seek to find a nonlinear transformation matrix, which can maximize the between-class scatter and minimize the within class scatter. First, we define the dot product in F as following.

$$k(x, y) = \phi(x).\phi(y) \quad (6)$$

Between-class scatter matrix S_B and within class scatter matrix S_W are defined in the feature space F:

$$S_w = \sum_{i=1}^{c} p(w_i)E((\phi(x) - u)(\phi(x) - u)^T) \quad (7)$$

$$S_B = \sum_{i=1}^{c} p(w_i)E(u_i - u)(u_i - u)^T) \quad (8)$$

III. FACE RECOGNITION TECHNIQUES

There are countless diverse face recognition techniques that pertain mostly to the frontal faces. This section gives an overview of all these techniques. The advantages and disadvantages of each technique are also discussed. The methods which are worn for the face detection are eigenfaces (eigenfeatures), Fisherfaces, Support vector machine and neural networks. The approaches are analyzed in terms of the facial representations they used.

A. Eigenfaces

Karhunen-Loeve is plinth on the eigenfaces technique in which the Principal Component Analysis (PCA) is used. This method is effectively used in order to execute dimensionality reduction. In mathematical terms definition, the eigenfaces are the key components of the distribution of faces. This is also called as the eigenvectors which is the covariance medium of the set of face images. Principal Component Analysis is used by Turk and Pentland for face recognition and detection [2]. The main goal of the PCA is to find the eigen-vectors, called as also "EigenFaces", of the covariance matrix corresponding to the standard training images (sample image). To show the different amount of the variation, the eigenvectors are ordered respectively, among the faces. All face can be measured as a linear combination of the eigenfaces. The face can be approximated by using the eigenvectors which have major eigenvalues. The best M eigenfaces define an M dimensional space, which is called as the "face space". Principal Component Analysis is also used by L. Sirovich and M. Kirby [25] to proficiently represent pictures of faces. They defined that a face images could be roughly re-enact with a small compilation of weights for each face and a typical face picture (eigenpicture). The weights relating each face are obtained by prognosticing the face image onto the eigenpicture.

B. Fisherfaces

Linear/Fisher Discriminant Analysis (LDA) was urbanized by R. A. Fisher in 1930 [26]. The Fisherface method is the face recognition method which is based on the manifestation. The Linear Discriminant analysis technique has shown the functional result in the face recognition process. The LDA has demonstrated in (Ye and Li., 2004) [27]. All of these have used Linear Discriminant Analysis (LDA) to uncover a set of basis images which impart the help to maximize the ratio of linking-class scatter to that of within-class scatter. There is one dilemma with LDA that inside the class the scatter matrix is always solitary since the number of pixels in image is larger than the number of images so it can boost detection of error rate if there is a distinction in pose or lighting condition within same face images. So to overcome the single matrix problem, numerous algorithms have been anticipated [28]. Because the fisherfaces approach use the benefit of within-class information so it minimizes the variation within each class, but due to it there is the increase in class separation. So the crisis with adaptation in the same images such as different lighting conditions can be triumph over.

C. Support Vector Machines

Support vector machines are learning machines that organize data by shaping a set of support vectors [29]. SVMs provide a standard mechanism to vigorous the surface of the hyper plane to the data from beginning to end. Another benefit of SVMs is the low predictable probability of simplification errors [30]. Furthermore, once the data is classified into two classes, an proper optimizing algorithm can be worn if needed for feature identification, depending on the application [31]. SVM creates a hyper-plane between two sets of data for classification; in our effort, we separate the data into two classes: face belongs to the train database and face doesn't belong to the train database. Input data X that go down one region of the hyper-plane, (XT•W– b) > 0, are labeled as +1 and those that drop on the other area, (XT•W– b) < 0, are labeled as -1.

D. Neural network

The purposes of neural networks are in many pattern recognition problems, like character recognition, object recognition, and autonomous robot driving. The main benefit of the neural network in the face recognition is the practicability of training a system to capture the complex class of face representation.
To acquire the best feat by the neural network, it has to be comprehensively tuned (number of layers, number of nodes, learning rates, etc.) [32]. Neural network is extensively used because it is nonlinear in the arrangement. So, the feature extraction step may be added proficiently than the linear Karhunen-Loève methods in a dimensionality dropping linear protuberance is selected which increase the scatter of all projected samples. The author's details that there was 96.2% accuracy in the face recognition process when 400 images of 40 individuals are measured. The classification time is less than 0.5 second, but the training time is as long as 4 hours facial appearance in a hierarchical set of layers and impart partial invariance to translation, rotation, scale, and deformation. In general, neural network loom encounter problems when the number of classes (i.e., individuals) increases.

Database used	**PCA**	**LDA**	**KPCA**	**KFA**
Original PGM ORL db	66.07 %	86.07%	49.29%	85.07%
Haar 10 de-noised DB	66.43%	89.29%	51.07%	86.07
de-noised DB by (Haar+Bior1.1)10	72.50%	90.71%	51.43%	88.57%
HE DB	66.43%	85.36%	50.36%	81.43%
Adjust DB	72.14%	88.21%	54.95%	87.86%
Adjust +hist DB	75.00%	91.43%	3.21%	86.43%

Table 1. Comparisons in the performance PCA, LDA, KPCA and KFA face recognition methods [26].

IV. CONCLUSION

This paper has attempted to review a significant number of papers to cover development in the field of human facial and voice recognition. Various techniques can be used for better recognition rate. Techniques with higher recognition rate have greater performance .These approaches provide a practical solution to the problem of facial expression recognition and can work well in constrained environment. Emotion detection using facial expression is a universal issue and causes difficulties due to uncertain physical and psychological characteristics of emotions that are linked to the traits of each person individually. Therefore, research in this field will remain under continuous study for many years to come because many problems have to be solved in order to create an ideal user interface and improved recognition of complex emotional states is required The list of references to provide more detailed understanding of the approaches described is enlisted. We apologize to researchers whose important contributions may have been overlooked.

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