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Kinship Verification

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***Abstract-* Kinship verification from facial images is a challenging problem in computer vision and research is going on in this area. In this system, we have used neighborhood repulsed metric learning (NRML) method for kinship verification. Motivated by the fact that interclass samples (without kinship relations) with higher similarity usually lie in a neighbourhood and are more easily misclassified than those with lower similarity. The proposed system uses this distance metric and classifies the test pair of images as kinship or non-kinship relation.**

***Index terms-* Kinship verification, NRML, Metric learning, distance metric**

I. INTRODUCTION

Facial images convey many important human characteristics, such as identity, gender, expression and so on. Over the past two decades, a large number of face analysis problems have been investigated in the computer vision and pattern recognition community, for examples, face recognition, facial expression recognition and facial age estimation gender classification. In this paper, we implement the system: kinship verification from facial images.

We examine in this paper two different types of kinship
relations: father-daughter (F-D) and mother-son (M-S) kinship relations. This system have applications such as family album organization, image annotation and missing children/parents search. We are using kinship database named KinFaceW-I from. Then, we a robust distance metric under which facial images with kinship relations are projected as close as possible and those without kinship relations are pushed away as far as possible, simultaneously. Since interclass samples (without a kinship relation) with higher similarity usually lie in a neighborhood and are more easily misclassified than those with lower similarity, we emphasize the interclass samples in a neighborhood more in learning the distance metric and expect those samples lying in a neighborhood are repulsed and pushed away as far as possible, simultaneously, such that more discriminative information can be exploited for verification.

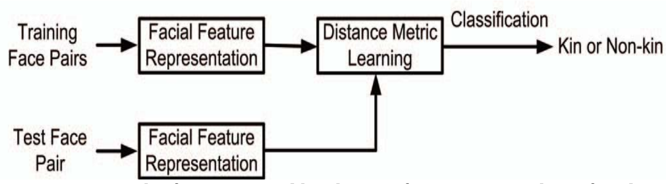

Fig.1. Framework of our proposed kinship verification approach via facial image analysis.

As shown in fig.1 given a set of training face images, we first extract features for each face image and learn a distance metric to map these feature representations into a low dimensional feature subspace, under which the kinship relation of face samples can be better discriminated. For each test face pair, we also extract features of each face image and map these features to the learned low-dimensional feature subspace. Finally, a classifier is used to verify whether there is a kinship relationship or not between the test face pair.

II. PROPOSED METHODS

A. Basic Idea

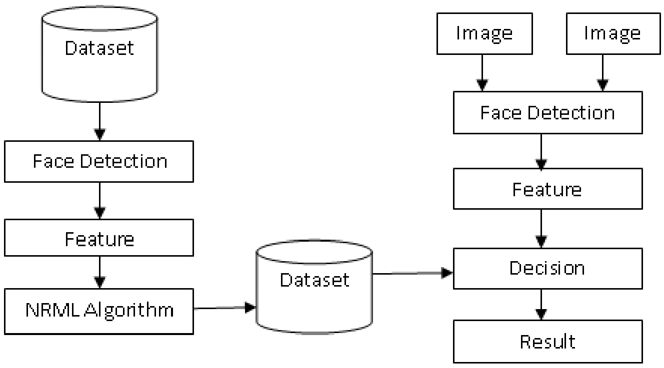

Fig.2. Block Diagram of Proposed System

Fig. 2 shows the block diagram of proposed system. As shown in the block diagram, In our system we first train the system on the dataset KinFaceW-I, which contains labelled pair of images. In real time execution two input images are given as input. Feature extraction is performed using algorithm such as average RGB, Co-occurance and Geometric Moment. The distance between inputs images is calculated which is input to the SVM. SVM classifier perform the classification and produces the output whether there exists kinship or not in the input pair of images.

Fig. 3. Several image examples of KinFaceW-I database. From top to bottom are the father-daughter (F-D) and mother-son(M-S) kinship relations, and the neighboring two images in each row are with kinship relation, respectively.

III. RELATED WORK

In this section, we briefly review two related topics: 1)kinship verification, and 2) metric learning.

A. *Kinship Verification*

Recent research in human perception of kinship verification has investigated that humans have the capability to recognize kinship based on face images even if these images are from unfamiliar faces. Motivated by this finding, researchers in computer vision are interested in developing computational approaches to verify human kinship relations, and there have been a limited number of attempts to address this problem in recent years. To solve this problem of kinship verification, we first extract some features such as skin color, texture, and face shape information to describe facial images. Then, the k-nearest-neighbour(KNN) and support vector machine(SVM) classifiers were applied to classify face images. There was method[2][3] invented few years before called a transfer subspace learning approach for kinship verification., in which basic idea is to utilize an intermediate young parent facial image set to reduce the divergence between the children and old parent images based on the assumption that the children and young parents possess more facial resemblance in facial appearances. While encouraging results were obtained, there are still shortcoming among the existing kinship verification works: The conventional euclidean metric was usually utilized for kinship verification and such metric is not appropriate to measure the similarity of facial images because the intrinsic space that face usually lies in is a low-dimensional manifold rather than a euclidean space; Hence, in our system, we are using more robust and effective distance metrics to improve the performance of kinship verification methods.

B. *Metric Learning*

There have been a number of metric learning algorithms in the literature, since metric learning has received a lot of attention in computer vision and machine learning in recent years. Existing metric learning methods can be divided into two categories: unsupervised and supervised. Unsupervised methods aim to learn a low-dimensional manifold where the geometrical information of the samples is preserved. Representatives of such algorithms include principal component analysis (PCA)[10], locally linear embedding (LLE)[8], multidimensional scaling(MDS)[11],etc. Supervised methods aim to seek an appropriate distance metric for classification tasks. Generally, an optimization objective function is formulated based on some supervised information of the training samples to learn the distance metric. The difference among these methods lies mainly in the objective functions, which are designed for their specific tasks. Typical supervised metric learning methods include linear discriminant analysis (LDA)[9], neighborhood component analysis (NCA)[7], cosine similarity metric learning (CSML)[4], large margin nearest neighbour (LMNN)[6], and information theoretic metric learning (ITML)[5]. While metric learning methods have achieved reasonably good performance in many visual analysis applications, there are still some shortcoming among most existing methods, Some training samples are more informative in learning the distance metric than others, and most existing metric learning methods consider them equally and ignore potentially different contributions of the samples to learn the distance metric.

IV. EXPERIMENTAL SETTINGS

A. *Data Sets*

We used data sets named KinFaceW-I from which contains images collected through an online search, where some are public figure face images, as well as their parents' or children's face images. In our system we are considering two kinship classes F-D and M-S. Hence we are using 128 pairs of father-daughter kinship images and 116 pairs of mother-son kinship images. The images in dataset are already converted in 64x64 pixel dimension.

B. *Feature Extraction*

Feature extraction module extracts the features such as color, shape and texture from images by using algorithms mentioned in this sections. In proposed system feature extraction return feature descriptor with 24 values.

Average RGB Algorithm: Average RGB is based on color centroids analysis and tracking. It is useful for multiple faces in different positions, scales and pose or the faces appear or disappear from sequence. This algorithm works on the principle of RGB values for each pixel and returns its value for each pixel by seen its color value. In proposed system this method works on the pixel color and returns 3 value in the feature vector.

Co-Occurrence Algorithm: Texture analysis characterizes the spatial variation of image pattern based on some mathematical procedures and models to extract information from it. Co-Occurrences Algorithm is used for texture analysis. It works on the liquid crystal value of the pixels. In this statistical parameters are calculated from the image intensity values without considering the pixel neighbour relationship. In proposed system feature extraction module returns 20 values for co-occurrence in feature vector.

Geometric Moment Algorithm: Geometric moment invariant produces a set of vectors that invariant under shifting, scaling and rotation. The technique is used to extract the global feature for pattern reorganization. It is specially used for shape detection. This method is used for calculating the extracted values of the moments. For any object image it requires only 2K operations, where K is the number of pixels on the both left and right boundary. In proposed system this method works on the moments of pixel and returns 1 value in feature vector.

C. *Classifier*

Since kinship verification is a binary classification problem and support vector machine (SVM) has demonstrated good performance for binary classification problem, we here use SVM for classification. The classes represent kinship and non kinship relation. SVM is trained on solution model which contains labelled kinship pairs. Using solution model SVM predicts the class of test image pair.

V. CONCLUSION

The main aim of this system is to predict whether kinship exists in the test pair of image. Proposed system comes under Computer Vision and is based on Face recognition, Feature extraction and knowledge transfer learning. The proposed system uses a distance metric which maps the face images in low-dimensional space. The system is trained on dataset by which SVM ultimately classifies the test pair in kinship or non kinship.

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