ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

Face Recognition Based on Kinship Using Distance Learning Approach

Divya Dharshini .N[1], Gomathy Nayagam. M[2],

M.E. Computer Science and Engineering, Department of Computer Science and Engineering, Mount Zion College of Engineering and Technology, Lena Vilakku Pilivalam (Post), Thirumayam TK, Pudukkottai, TamilNadu, India.

Assistant Professor, Department of Computer Science and Engineering, Mount Zion College of Engineering and Technology, Lena Vilakku Pilivalam (Post), Thirumayam TK, Pudukkottai, TamilNadu, India.

ABSTRACT: Due to the fact that rich human characteristics, such as gender, identity, expression, and ethnicity, can be effectively extracted from facial images, a variety of face analysis problems, ranging from face recognition, facial expression recognition, and gender estimation to age estimation, have been extensively studied over the past decades. Kinship verification using facial images, however, is a relatively new and challenging problem in biometrics, which is mainly motivated by the phenomenon that children generally look like their parents more than other people due to the kinship relation. The aim of the kinship verification via biometrics is to determine whether a given pair of face images of two people has a kin relationship. Most existing methods for kinship verification assume that each positive pair of face images (with kin relationship) has greater similarity score than those of negative pairs without kin relationships under a distance metric to be learned. In practice, however, this assumption is usually too strict for real-life kin samples. Instead, we propose in this project learning a robust similarity model which includes discriminative deep metric learning (DDML) method for face and kinship verification, under which the similarity score of each positive pair is greater than average similarity score of some negative ones. In addition, we develop an online similarity learning algorithm for more scalable application. We empirically evaluate the proposed methods on real time database.

KEYWORDS: Face verification, kinship verification, deep learning, metric learning, multi-feature learning.

I. INTRODUCTION

The major objectives of the proposed system are summarized below: (a) Learning-based approaches, however, are focused on learning a genetic measure via training data based on some discriminative learning technologies, such as subspace learning and distance metric learning, to improve the reparability of facial images for kinship verification, (b) Despite the promising results by existing learning-based approaches to kinship verification, they aim to learn a distance metric (or transform) in a batch learning way, leading to less efficiency or scalability even for medium scale application, (c) DDML learns a set of hierarchical nonlinear transformations by a neural network to project face images into discriminative feature subspaces, so that both the nonlinear and scalability problems can be explicitly simultaneously addressed and (d) We develop a discriminative deep multi-metric learning (DDMML) method to jointly learn multiple neural networks to exploit the common information to improve the verification performance.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

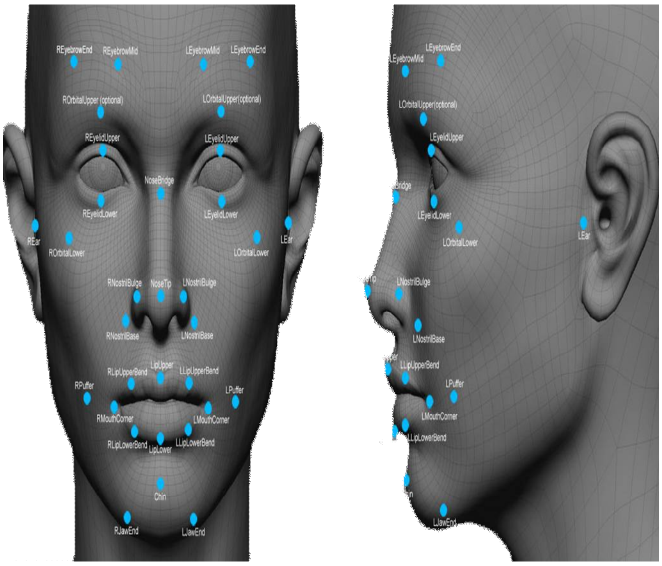

Fig.1 Facial Point Detection

In recent years face recognition has received substantial attention from researchers in biometrics, pattern recognition, and computer vision communities. The machine learning and computer graphics communities are also increasingly involved in face recognition. This common interest among researchers working in diverse fields is motivated by our remarkable ability to recognize people and the fact that human activity is a primary concern both in everyday life and in cyberspace. Besides, there is a large number of commercial, securities, and forensic applications requiring the use of face recognition technologies. These applications include automated crowd surveillance, access control, mug shot identification (e.g., for issuing driver licenses), face reconstruction, design of human computer interface (HCI), multimedia communication (e.g., generation of synthetic faces), and content-based image database management. A face recognition system is a computer application capable of identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a face database.

It is typically used in security systems and can be compared to other biometrics such as fingerprint or eye iris recognition systems. Recently, it has also become popular as a commercial identification and marketing tool. Face identification (”Who am I?”) is a one-to-many matching process that compares a query face image against all the template images in a face database to determine the identity of the query face. The identification of the test image is done by locating the image in the database that has the highest similarity with the test image. The identification process is a “closed” test, which means the sensor takes an observation of an individual that is known to be in the database. The test subject’s (normalized) features are compared to the other features in the system’s database and a similarity score is found for each comparison. These similarity scores are then numerically ranked in a descending order. The percentage of times that the highest similarity score is the correct match for all individuals is referred to as the “top match score.” If any of the top r similarity scores corresponds to the test subject, it is considered as a correct match in terms of the cumulative match. The percentage of times one of those r similarity scores is the correct match for all individuals is referred to as the”Cumulative Match Score”. The “Cumulative Match Score” curve is the rank n versus percentage of correct identification, where rank n is the number of top similarity scores reported.

II. EXISTING APPROACHES – A SUMMARY

Past Systems proposed a spatial pyramid learning based (SPLE) feature descriptor and a Gabor-based Gradient Orientation Pyramid (GGOP) feature to represent facial images integrated with support vector machine (SVM)

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

classifier for kinship verification. The above-mentioned methods are all feature-based with the aim of extracting some discriminative features to describe facial images, in which each face image is represented as a compact feature vector; meanwhile, intra-class variations are reduced and interclass variations are increased as much as possible and applied to many computer vision problems, such as neighborhood component analysis (NCA), large margin nearest neighbor (LMNN), information theoretic metric learning (ITML), cosine similarity metric learning (CSML), large scale metric learning (LSML), sparse pairwise constraints metric learning (SPCML), neighborhood repulsed metric learning (NRML), and discriminative multi-metric learning (DMML), while most existing distance metric learning methods generally are designed to learn a $d\times d$ distance metric square matrix. If feature descriptor has large dimensionality, the metric learning algorithm will have a very high computation cost. The existing approaches contains lots of disadvantages, some of them are listed below: (a) Difficult to verify the kinship, (b) High complexity, (c) Delay time at verification and (d) Large number of facial features.

III. PROPOSED SYSTEM SUMMARY

Metric learning has been widely used in face and kinship verification and a number of such algorithms have been proposed over the past decade. However, most existing metric learning methods only learn one distance metric from a single feature representation for each face image and cannot deal with multiple feature representations directly. In many face verification applications, we have access to extract multiple features for each face image to extract more complementary information, and it is desirable to learn distance metrics from these multiple features so that more discriminative information can be exploited than those learned from individual features.

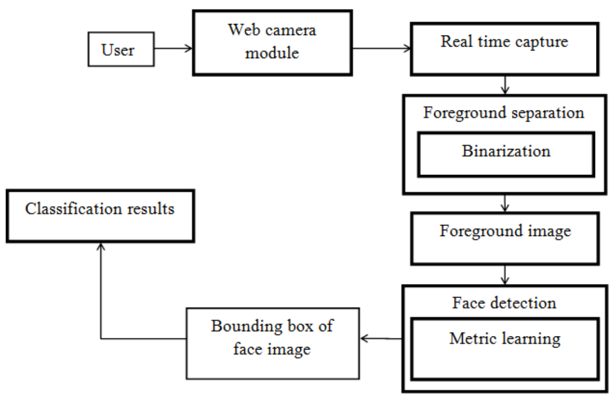

Fig.2 Proposed System Architecture

Face recognition can be mainly classified into two tasks: face identification and face verification. The former aims to recognize the person from a set of gallery face images or videos and find the most similar one to the probe sample. The latter is to determine whether a given pair of face images or videos is from the same person or not. In this paper, we consider the second one where face images contain significant variations caused by varying lighting, expression, pose, resolution, and background. . Unlike most existing metric learning methods, our DDML builds a deep neural network which learns a set of hierarchical nonlinear transformations to project face pairs into other feature subspace, under which the distance of each positive face pair is less than a smaller threshold and that of each negative pair is higher than a larger threshold, respectively, so that discriminative information is exploited for the verification task.

The common objective of these methods is to learn a good distance metric so that the distance between positive face pairs is reduced and that of negative pairs is enlarged as much as possible. However, most existing metric learning methods only learn a linear transformation to map face samples into a new feature space, which may not be powerful enough to capture the nonlinear manifold where face images usually lie on real time databases. The Proposed

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

approach contains lots of advantages; some of them are listed below: (a) Less complexity, (b) Accuracy high and (c) Learning based analysis for kinship verification.

IV. SYSTEM IMPLEMENTATION

The proposed system is designed with lots of purposeful modules that are described in detail:

A. Face Image Acquisition

The first stage of any vision system is the image acquisition stage. After the image has been obtained, various methods of processing can be applied to the image to perform the many different vision tasks required today. However, if the image has not been acquired satisfactorily then the intended tasks may not be achievable, even with the aid of some form of image enhancement. The basic two-dimensional image is a monochrome (greyscale) image which has been digitized. Describe image as a two-dimensional light intensity function f(x,y) where x and y are spatial coordinates and the value of f at any point (x, y) is proportional to the brightness or grey value of the image at that point. A digitised image is one where: (a) spatial and gray scale values have been made discrete, (b) intensity measured across a regularly spaced grid in x and y directions and (c) intensities sampled to 8 bits (256 values). In this module, we can capture the face images through web cameras in real time. Capture image can by any type and any size.

B. Pre-Processing

Background subtraction, also known as foreground detection, is a technique in the fields of image processing and computer vision wherein an image's foreground is extracted for further processing (object recognition etc.). Generally an image's regions of interest are objects (humans, cars, text etc.) in its foreground. After the stage of image preprocessing (which may include image denoising, post processing like morphology etc.) object localization is required which may make use of this technique. Background subtraction is a widely used approach for detecting moving objects in videos from static cameras. The rationale in the approach is that of detecting the moving objects from the difference between the current frame and a reference frame, often called "background image", or "background model". Background subtraction is mostly done if the image in question is a part of a video stream. In this module we can implement binarization algorithm to separate the foreground from back ground. File picture binarization is performed within the preprocessing stage for record analysis and it ambitions to section the foreground data from captured image.

C. Facial Features Extraction

In this module implement Discriminative Deep Metric Learning's which are an algorithm employed the computer technology that determines the locations and sizes of human faces in arbitrary (digital) images. It detects facial features and ignores anything else, such as buildings, trees and bodies. Face detection can be regarded as a more general case of face localization. In face localization, the task is to find the locations and sizes of a known number of faces (usually one).

D. Distance Metrics Evaluation

A metric or distance function is a function that defines a distance between each pair of elements of a set. Distance Metric learning is to learn a distance metric for the input space of data from a given collection of pair of similar/dissimilar points that preserves the distance relation among the training data. . For instance, for the area close to the decision boundary between two classes, we expect the class labels to change dramatically even within a range of short distance. In order to preserve the smoothness of neighborhood in terms of class conditional probability, we can elongate the distance where the change of label tends to be large such that the data points having inconsistent labeling as the query point are excluded from the neighbor of the query example.

E. Classification Results

In this module, implement classification approach to analyze the relationship of each image. Face images are matched with existing database using classifier approach. An algorithm that implements classification, especially in a concrete implementation, is known as a classifier. The term "classifier" sometimes also refers to the mathematical

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

function, implemented by a classification algorithm that maps input data to a category. In the meantime, we can also squeeze the distance to include more points into the neighborhood of the query point if they share the same class labels as the query point. Finally provide face images with relationships.

V. LITERATURE SURVEY

In the year of 2014, the authors "J. Hu, J. Lu, and Y.-P. Tan" proposed a paper titled “Discriminative deep metric learning for face verification in the wild", in that they described such as: we have presented a new discriminative deep metric learning (DDML) method for face verification in the wild. Our method achieves the very competitive verification performance on the widely used LFW and YTF datasets. How to apply our DDML method to other visual applications such as image classification and activity recognition is an interesting direction of future work.

In the year of 2013, the authors "J. Lu, Y.-P. Tan, and G. Wang" proposed a paper titled “Discriminative multimanifold analysisfor face recognition from a single training sample per person", in that they described such as: a novel discriminative multi-manifold analysis (DMMA) method to address the SSPP problem in face recognition. We partition each enrolled image into several non-overlapping patches, and construct an image set for each sample per person, and then learn multiple feature spaces to maximize the manifold margins of different persons.

In the year of 2010, the authors "R. Fang, K. Tang, N. Snavely, and T. Chen" proposed a paper titled “Towards computational models of kinship verification", in that they described such as: a lightweight facial feature extraction algorithm and forward selection methodology to tackle the challenge of kinship verification and find the most discriminative inherited facial features. We have first conducted a controlled on-line image search to collect 150 facial images of parents and children pairs of public figures. The database was collected such that it has a wide spread distribution on facial characteristics which depend on race, gender, age, career, etc.

VI. EXPERIMENTAL RESULTS

The following figure illustrates the Face Detection Scheme of the proposed system.

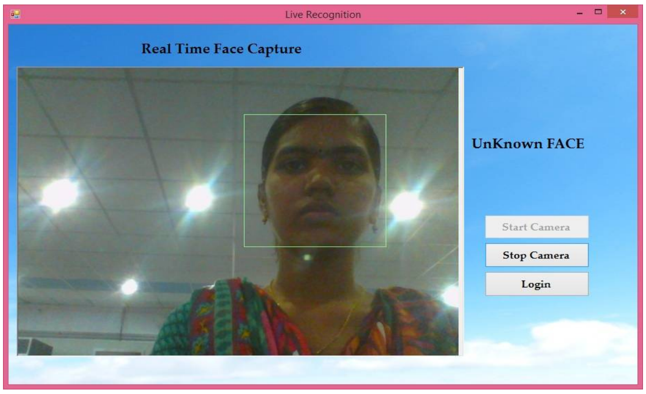

Fig.3 Face Detection Scheme

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

The following figure illustrates the new user Registration Scheme.

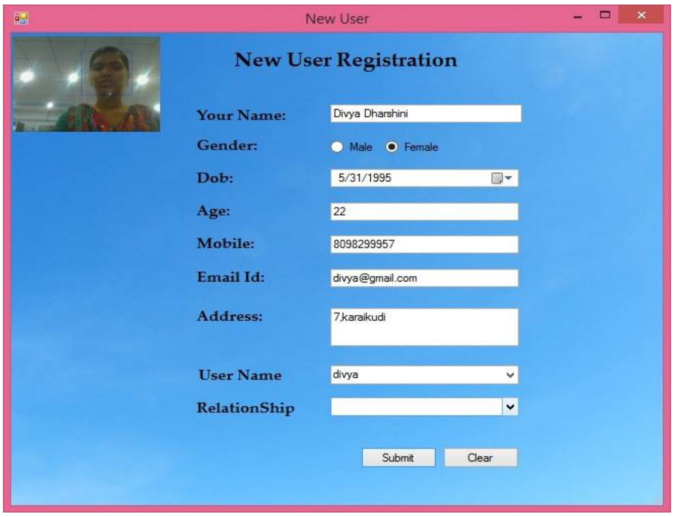

Fig.4 Registration Page

The following figure illustrates the face verification scheme of the proposed system.

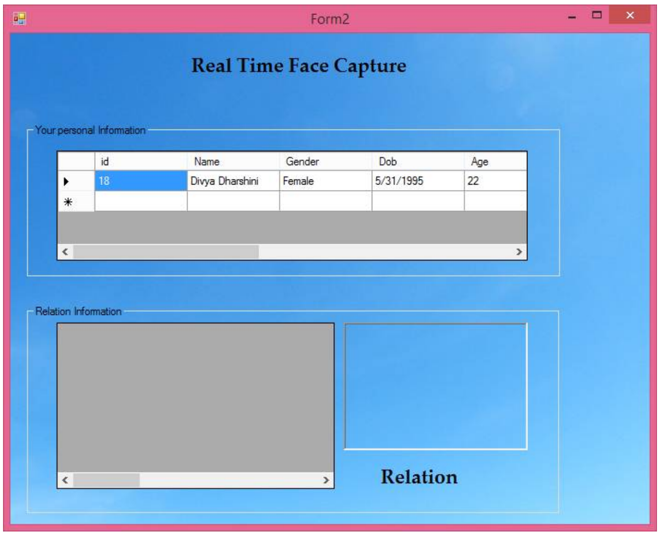

Fig.5 Face Verification Scheme

VII. CONCLUSION

In this project, we have proposed Discriminative Deep Metric Learning to address kinship verification via facial image analysis. The proposed model generates effective high-level features related with key-points based representations. Our proposed DMML method can obtain comparable kinship verification performance to that of human observers, which further demonstrates the feasibility of verifying human kinship via facial image analysis and the efficacy of our proposed method for practical applications. We first extracted multiple features using different feature descriptors to characterize the face image from different aspects for each face image. Then, we jointly learn

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 2, February 2018

multiple distance metrics (one for each feature), under which the probability of each pair of positive sample having a smaller distance than that of the most similar negative samples is maximized.

Moreover, we expect the correlation of different features of the same image is maximized in the learned distance metrics DMML outperforms the other compared multi-metric learning methods on our kinship verification task. That is because our method jointly learns multiple distance metrics such that the interactions of different metrics can be well exploited. Verifying human kinship relation in the same photo can obtain higher accuracy than in different photos. That is because face images collected from the same photo can reduce some challenges caused by the illumination and aging variations. Experimental results demonstrate that the proposed method largely enhances the state-of-the-art performance, and outperforms human performance

REFERENCES

[1] J. Hu, J. Lu, and Y.-P.Tan, “Discriminative deep metric learning for face verification in the wild,” in IEEE Conference on Computer Visionand Pattern Recognition, 2014, pp. 1875–1882.
[2] J. Lu, Y.-P. Tan, and G. Wang, “Discriminative multimanifold analysis for face recognition from a single training sample per person,” IEEETransactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 1, pp. 39–51, 2013.
[3] R. Fang, K. Tang, N. Snavely, and T. Chen, “Towards computational models of kinship verification,” in International Conference on ImageProcessing, 2010, pp. 1577–1580.
[4] S. Xia, M. Shao, J. Luo, and Y. Fu, “Understanding kin relationships in a photo,” IEEE Transactions on Multimedia, vol. 14, no. 4, pp. 1046–1056, 2012.
[5] J. Lu, J. Hu, X. Zhou, Y. Shang, Y.-P. Tan, and G. Wang, “Neighborhood repulsed metric learning for kinship verification,” in IEEE Conferenceon Computer Vision and Pattern Recognition, 2012, pp. 2594–2601.
[6] L. Wolf, T. Hassner, and I. Maoz, “Face recognition in unconstrained videos with matched background similarity,” in IEEE Conference onComputer Vision and Pattern Recognition, 2011, pp. 529–534.
[7] K. Simonyan, O. M. Parkhi, A. Vedaldi, and A. Zisserman, “Fisher vector faces in the wild,” in British Machine Vision Conference, 2013, pp. 1–12.
[8] L. Wolf and N. Levy, “The svm-minus similarity score for video face recognition,” in IEEE Conference on Computer Vision and PatternRecognition, 2013, pp. 3523–3530.
[9] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” International Journal of Computer Vision, vol. 60, no. 2, pp. 91–110, 2004.
[10] Z. Lei, M. Pietik¨ainen, and S. Z. Li, “Learning discriminant face descriptor,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, no. 2, pp. 289–302, 2014.
[11] H. V. Nguyen and L. Bai, “Cosine similarity metric learning for face verification,” in Asian Conference on Computer Vision, 2010, pp. 709–720.
[12] X. Zhou, J. Hu, J. Lu, Y. Shang, and Y. Guan, “Kinship verification from facial images under uncontrolled conditions,” in ACM Conferenceon Multimedia, 2011, pp. 953–956.
[13] X. Zhou, J. Lu, J. Hu, and Y. Shang, “Gabor-based gradient orientation pyramid for kinship verification under uncontrolled environments,” in ACM Conference on Multimedia, 2012, pp. 725–728.
[14] G. Somanath and C. Kambhamettu, “Can faces verify blood-relations?” in IEEE International Conference on Biometrics: Theory, Applicationsand Systems, 2012, pp. 105–112.
[15] H. Dibeklioglu, A. A. Salah, and T. Gevers, “Like father, like son: Facial expression dynamics for kinship verification,” in IEEE InternationalConference on Computer Vision, 2013, pp. 1497–1504.