Discriminative Multimetric Learning for Kinship Verification

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***Abstract*— In this paper, we propose a new discriminative multimetric learning method for kinship verification via facial image analysis. Given each face image, we first extract multiple features using different face descriptors to characterize face images from different aspects because different feature descriptors can provide complementary information. Then, we jointly learn multiple distance metrics with these extracted multiple features under which the probability of a pair of face image with a kinship relation having a smaller distance than that of the pair without a kinship relation is maximized, and the correlation of different features of the same face sample is maximized, simultaneously, so that complementary and discriminative information is exploited for verification. Experimental results on four face kinship data sets show the effectiveness of our proposed method over the existing single-metric and multimetric learning methods.**

***Index Terms*— Kinship verification, multi-metric learning, discriminative learning, face recognition, biometrics.**

I. INTRODUCTION

RECENT advances in psychology [2], [5], [6], [8], [15], [16] have shown that human facial appearance is an important cue for genetic similarity measure because children and their parents are biologically related and children usually resemble their parents more than other adults. Motivated by this finding, computer vision researchers have investigated the problem of kinship verification via facial image analysis over the past five years [9], [10], [13], [20], [23], [28], [35], [36], [40], [41]. While some encouraging results have been obtained, this problem still remains unsolved especially when face images were captured in unconstrained environments. This is because varying poses, illumination, expressions, and aging usually occur in the collected face images in such scenarios, which makes this problem extremely challenging.

Fig. 1. Some sample positive pairs (with kinship relation) from different face kinship databases. Face images from the first to fourth row are from the KinFaceW-I [23], KinFaceW-II [23], Cornell KinFace [10] and UB KinFace [35] datasets, respectively.

In this paper, we propose a discriminative multi-metric learning (DMML) method for kinship verification via facial images. Fig. 1 shows some sample positive pairs from different kinship databases. Our approach is motivated by the following two intrinsical characteristics of this challenging problem:

- Since the intra-class variation (the difference of face images with kinship relation) is usually large and even higher than the inter-class variation (the difference of face images without kinship relation), the kinship relation cannot be well represented by the original feature space and it is desirable to learn a semantic space to better characterize the kinship relation.
- Since different feature descriptors can characterize face images from different aspects, we extract multiple features to exploit more complementary information to improve the kinship verification performance.

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To achieve this, for each given face image, we first extract multiple features using different feature descriptors to characterize the face image from different aspects for each face image. Then, we jointly learn 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. Experimental results on four publicly available face kinship databases are presented to demonstrate the efficacy of the proposed method. Lastly, we test human ability in kinship verification and our experimental results show that our method is comparable to that of human observers.

The rest of the paper is organized as follows. Section II discusses related work. Section III details our proposed approach. Section IV provides the experimental results, and Section V concludes the paper.

II. Related Work

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

A. Kinship Verification

There have been several seminal attempts on kinship verification via facial images over the past five years [9], [10], [13], [17], [23], [28], [35], [36], [40], [41], and these methods can be roughly classified into two categories: 1) feature-based [10], [13], [40], [41], and 2) learning-based [23], [28], [35], [36]. For feature-based methods, some discriminative feature representations were applied to characterize facial images, such as skin color [10], histogram of gradient [10], Gabor gradient orientation pyramid [41], salient part and self-similarity [13], and dynamic expressions [9]. For learning-based methods, some discriminative learning algorithms such as subspace learning [28], [35] and metric learning [23] were used to seek a semantic subspace to enhance the separability of face images for kinship verification. Unlike these previous studies [10], [13], [17], [23], [28], [35], [36], [40], [41], in this work, we extract multiple features for each face image and learn multiple discriminative metrics for the kinship verification problem. Since more complementary information can be well exploited and combined, our method achieves state-of-the-art performance on the existing benchmark face kinship datasets.

B. Metric Learning

Many metric learning algorithms [12], [18], [18], [24], [30], [37], [39] have been proposed in recent years, and they have been successfully used in many computer vision tasks such as face recognition [12], [18], gait recognition [22], human activity recognition [30], human age estimation [37], and person re-identification [18], [24], [39]. Most existing metric learning methods only learn a Mahalanobis distance from a single feature space and cannot handle multi-feature representations directly. To address this, several multi-task metric learning methods [14], [27] which modeling the information sharing among different features have been proposed more recently. However, the interaction of different metrics has not been well exploited in these methods. More recently, several multi-metric learning methods have been proposed [25], [34], where a set of local distance metrics are first learned from each training sample/cluster, and then ensemble learning is applied to integrate local classifier in a probabilistic framework. Unlike existing multi-metric learning methods which aim to exploit more geometrical information in learning distance metrics, in this work, we propose a discriminative multi-metric learning (DMML) method to simultaneously learn multiple distance metrics, one for each feature descriptor, to exploit complementary information to better describe face images for kinship verification.

III. Approach

A. DMML

Let $S = \{(x_i, y_i)|i = 1, 2, \ldots, N\}$ be the training set of N pairs of face images with kinship relation (positive image pairs), where x_i and y_i are face images of the ith parent and child, respectively. For each face image, assume there are K different features extracted and $S^k = \{(x_i^k, y_i^k)|i = 1, 2, \ldots, N\}$ is the kth feature representation. Different from most previous metric learning algorithms which minimizing inter-class variation and maximizing intra-class variation simultaneously [7], [12], [26], [33], we aim to learn multiple distance metrics from these multiple features under which the probability of each positive image pair having a smaller distance than that of each negative pair is maximized, so that it is more robust to face appearance change and less susceptible to over-fitting. Specifically, for a positive image pair (x_i^k, y_i^k) in the kth feature representation space, we learn a distance function $g^k(\cdot)$ such that $g(x_i^k, y_i^k) < g(x_i^k, y_j^k)$ and $g(x_i^k, y_i^k) < g(x_l^k, y_i^k)$, where x_l and y_j are the parent and child images of any other person except the ith person in the training set, $1 \leq j, l \leq N$, and $j, l \neq i$. To achieve this, we measure the probability of the distance between a positive pair being smaller than that of a negative pair which share a same parent or child image as follows:

$$\begin{aligned} &P\big(g(x_i^k, y_i^k) < g(x_i^k, y_j^k)\big) \\ &\quad = \big(1 + \exp(g(x_i^k, y_i^k) - g(x_i^k, y_j^k))\big)^{-1} \end{aligned} \tag{1}$$

$$\begin{aligned} &P\big(g(x_i^k, y_i^k) < g(x_l^k, y_i^k)\big) \\ &\quad = \big(1 + \exp(g(x_i^k, y_i^k) - g(x_l^k, y_i^k))\big)^{-1} \end{aligned} \tag{2}$$

where

$$g(x_i^k, y_i^k) = (x_i^k - y_i^k)^T M_k (x_i^k - y_i^k) \tag{3}$$

where M_k is a semi-definite matrix learned for the kth feature representation.

We assume the distance comparison of each positive and negative pair is independent, i.e., $g(x_i^k, y_i^k) < g(x_i^k, y_j^k)$ and $g(x_i^k, y_i^k) < g(x_l^k, y_i^k)$ are independent. Based on the maximum likelihood principle, we formulate our proposed DMML method as the following constrained optimization problem:

$$\min_{M_1,\ldots,M_K,\alpha} J = \sum_{k=1}^{K} \alpha_k f_k(M_k) + \lambda g_k(W_1,\ldots,W_K)$$
$$\text{subject to} \quad \sum_{k=1}^{K} \alpha_k = 1, \alpha_k \geq 0. \tag{4}$$

where

$$f_k(M_k) = -\log\Big(\prod_{O_1^k} P\big(g(x_i^k, y_i^k) < g(x_i^k, y_j^k)\big)\Big) - \log\Big(\prod_{O_2^k} P\big(g(x_i^k, y_i^k) < g(x_l^k, y_i^k)\big)\Big) \tag{5}$$

$$g_k(W_1,\ldots,W_K) = \sum_{\substack{k_1,k_2=1\\k_1\neq k_2}}^{K} \sum_{i=1}^{N} \|W_{k_1}^T x_i^{k_1} - W_{k_2}^T x_i^{k_2}\|_F^2 \tag{6}$$

W_k is a low-dimensional subspace decomposed from M_k, where $M_k = W_k W_k^T$. O_1^k and O_2^k are the pairwise sets of the kth feature representation, $\alpha = [\alpha_1,\ldots,\alpha_K]$ is the weight vector and α_k is the weight of the kth feature, $\lambda > 0$ is a trade-off parameter to balance the two terms in the objective function. The first term in (4) is to ensure that the probability of the distance between a positive pair being smaller than that of a negative pair is as large as possible, so that discriminative information can be exploited. The second term in (4) is to ensure that the correlations of different feature representations of each sample are maximized to extract complementary information.

Since kinship verification is an under-sampled computer vision problem, most conventional metric learning methods [4], [7], [11], [12], [26], [30], [33], [38] are easily over-fitted if the distance metric is learned by directly minimizing intra-class distance and maximizing inter-class distance simultaneously. Unlike these methods, our DMML seeks the distance metrics under which the probability of each positive image pair having a smaller distance than that of each negative pair is maximized, such that it is less susceptible to over-fitting. On the other hand, the physical meaning of the second term in (4) is that we aim to learn K distance low-dimensional feature subspaces W_k ($k = 1,2,\ldots,K$) under which the difference of feature representations of the same sample is enforced to be as small as possible, which is consistent to the canonical correlation analysis (CCA)-like multiple feature fusion approach [29]. For CCA-based feature fusion, different feature representations are combined by jointly learning a common subspace under which the correlation of different feature representations of the same sample is maximized. In our model, the reason we used the difference of each pair of feature descriptors for the same sample rather than the correlation to measure the similarity of different feature representations in the low-dimensional subspace is that such a pairwise difference is very easy to compute the gradient in the optimization procedure.

Now, (4) can be rewritten as

$$\min_{W_1,\ldots,W_K,\alpha} J = \sum_{k=1}^{K} \alpha_k f_k(W_k) + \lambda \sum_{\substack{k_1,k_2=1\\k_1\neq k_2}}^{K} \sum_{i=1}^{N} |W_{k_1}^T x_i^{k_1} - W_{k_2}^T x_i^{k_2}\|_F^2 \tag{7}$$

where

$$f_k(W_k) = \prod_{O_1^k} \log(1 + \exp(\|W_k^T x_{ik}^p\|^2 - \|W_k^T x_{ik}^n\|^2)) \tag{8}$$

and $x_{ik}^p = x_i^k - y_i^k$, $x_{ik}^n = x_i^k - y_j^k$.[1]

There is no closed-form solution to the problem defined in (7) since there are K matrices and one vector to be optimized simultaneously. In this paper, we employ an alternating optimization method to get a local optimal solution. Specifically, we first initialize $W_1,\ldots,W_{k-1},W_{k+1},\ldots,W_K$ and α and solve W_k sequentially. Then, we update α accordingly.

Given $W_1,\ldots,W_{k-1},W_{k+1},\ldots,W_K$ and α, Eq. (7) can be rewritten as

$$\min_{W_k} J(W_k) = \alpha_k f_k(W_k) + \lambda \sum_{l=1,l\neq k}^{K} G(W_k) \tag{9}$$

where

$$G(W_k) = \sum_{i=1}^{N} \|W_k^T x_i^k - W_l^T x_i^l\|_2^2 \tag{10}$$

Since (9) is also not convex, it is non-trivial to get a global optimization solution. In this work, we propose a gradient-based optimization method by differentiating $f_k(W_k)$ and $G(W_k)$ with respect to W_k as follows:

$$\frac{\partial f_k(W_k)}{\partial W_k} = \prod_{O_1^k} \frac{2 + \exp(\|W_k^T x_{ik}^p\|^2 - \|W_k^T x_{ik}^n\|^2)}{1 + \exp(\|W_k^T x_{ik}^p\|^2 - \|W_k^T x_{ik}^n\|^2)} \times (x_{ik}^p x_{ik}^{pT} - x_{ik}^n x_{ik}^{nT}) W_k \tag{11}$$

$$\frac{\partial G(W_k)}{\partial W_k} = 2\lambda(K-1) W_k \sum_{i=1}^{N} (x_i^k)^T x_i^k - 2\lambda W_k \sum_{\substack{l=1\\l\neq k}}^{K} \sum_{i=1}^{N} (x_i^l)^T x_i^l \tag{12}$$

Hence, we can update W_k by using the following gradient descent method:

$$W_k^{t+1} = W_k^t - \eta\Big(\alpha_k \frac{f_k(W_k)}{W_k} + \lambda \sum_{l=1,l\neq k}^{K} \frac{\partial G(W_k)}{\partial W_k}\Big) \tag{13}$$

where $\eta > 0$ is a step length parameter to control the gradient descent speed. The iteration is terminated when the following criterion is satisfied:

$$J(W_k^t) - J(W_k^{t+1}) < \varepsilon \text{ or } \|W_k^{t+1} - W_k^t\| < \varepsilon \tag{14}$$

where ε is a small tolerance value set to 10^{-3} in this work.

[1] Since O_1^k and O_2^k are the same because they are generated from the same parents and children image sets, we only optimize the distance constraints in the O_1^k pairwise set.

Algorithm 1 DMML

Input: Training set $S = \{(x_i, y_i)|i = 1, 2, \ldots, N\}$, iteration number M and convergence error ε.
Output: Mapping matrices $W_1, W_2, \ldots, W_K$ and the weighting vector α.
Step 1 (Initialization):
Set $W_k^0 = I^{d\times d}$ and $\alpha = [1/K, \cdots, 1/K]$.
Step 2 (Local optimization):
For $m = 1, 2, \cdots, M$, repeat
2.1. Compute W_k^m according to (11)-(13).
2.2. Compute α according to (20).
2.3. If $m > 2$ and (14) is satisfied, go to Step 3.
Step 3 (Output mapping matrices):
Output mapping matrices $W_k = W_k^m$.

Having obtained W_1, W_2, ..., W_K, α can be updated by solving the following optimization problem

$$\min_{\alpha} \quad J(\alpha) = \sum_{k=1}^{K} \alpha_k f_k(W_k)$$
$$\text{subject to} \quad \sum_{k=1}^{K} \alpha_k = 1, \quad \alpha_k > 0. \tag{15}$$

The solution to (15) is $\alpha_k = 1$ corresponding to the maximal $f_k(W_k)$ over different features, and $\alpha_k = 0$ otherwise. This solution corresponds to selecting the best feature and ignores exploiting the complementary information of different features. To overcome this limitation, we revisit α_k as α_k^r, where $r > 1$, and present the following alternative objective function:

$$\min_{\alpha} \quad J(\alpha) = \sum_{k=1}^{K} \alpha_k^r f_k(W_k)$$
$$\text{subject to} \quad \sum_{k=1}^{K} \alpha_k = 1, \quad \alpha_k > 0. \tag{16}$$

The Lagrange function can be constructed as:

$$L(\alpha, \zeta) = \sum_{k=1}^{K} \alpha_k^r f_k(W_k) - \zeta(\sum_{k=1}^{K} \alpha_k - 1) \tag{17}$$

Let $\frac{\partial L(\alpha,\zeta)}{\partial \alpha_k} = 0$ and $\frac{\partial L(\alpha,\zeta)}{\partial \zeta} = 0$, we have

$$r\alpha_k^{r-1} f_k(W_k) - \zeta = 0 \tag{18}$$
$$\sum_{k=1}^{K} \alpha_k - 1 = 0 \tag{19}$$

Combining (18) and (19), we can obtain α_k as follows

$$\alpha_k = \frac{(1/f_k(W_k))^{1/(r-1)}}{\sum_{k=1}^{K}(1/f_k(W_k))^{1/(r-1)}} \tag{20}$$

Having obtained α, we can update W_k by using Eq. (9). **Algorithm 1** summarizes the proposed DMML method.

B. Implementation Details

We apply three different feature descriptors including Local Binary Patterns (LBP) [1], Spatial Pyramid LEarning (SPLE) [40] and Scale-Invariant Feature Transform (SIFT) [19] to extract different and complementary information from each face image. The reason we selected these three features is that they have shown reasonably good performance in recent kinship verification works [23], [40]. No doubt, more effective feature descriptors could be employed to improve the verification performance. However, the main interest in this study is to evaluate the proposed DMML method which uses multiple features for kinship verification.

For each face image, we employed 256 bins to extract the LBP feature. For the SPLE feature, three different resolutions are first constructed and 21 cells are obtained. Then, each local feature in each cell was quantized into 200 bins and each face image was represented by a 4200-dimensional long feature vector. For the SIFT feature, each SIFT descriptors was first sampled over each 16×16 patch with a grid spacing of 8 pixels. Then, each SIFT descriptor is concatenated into a long feature vector. For these features, we apply Principal Component Analysis (PCA) [31] to reduce each feature into 200 dimensions to remove some noise components.

C. Discussion With Previous Work

Our method is intrinsically different from previous multi-metric learning methods [21], [25], [32], [34]. The method in [25] learns a set of local distance metrics from each training example and applies ensemble learning to combine the learned local metrics. The method in [34] partitions the training data into disjoint clusters and learns a distance metric for each cluster, and then the cluster-dependent distance metric is used for classification. The methods in [21] and [32] learn multiple class-specific distance metrics for recognition, so that the data heterogeneity can be alleviated. Unlike these existing multiple metric learning methods which aim to handle the data nonlinearity in learning distance metrics and have not well exploited the interaction of different distance metrics, our DMML method simultaneously learns multiple distance metrics, one for each feature descriptor, to exploit more complementary information to better describe face images. Hence, our method is more suitable for multi-feature based distance metric learning, and is complementary to existing multiple metric learning methods.

IV. Experiments

In this section, we conducted extensive kinship verification experiments on four publicly available face kinship datasets to show the effectiveness of our proposed DMML method. The following details the experimental settings and results.

A. Data Sets

Four publicly available face kinship datasets, KinFaceW-I [23],[2] KinFaceW-II [23],[3] Cornell KinFace [10][4] and

[2]https://sites.google.com/site/elujiwen/download.
[3]https://sites.google.com/site/elujiwen/download.
[4]http://chenlab.ece.cornell.edu/projects/KinshipVerification.

UB KinFace [35],[5] were used for evaluation. There are four kinship relations in all these datasets: Father-Son (F-S), Father-Daughter (F-D), Mother-Son (M-S), and Mother-Daughter (M-D). There are 156, 134, 116, and 127 pairs of kinship images in KinFaceW-I for these four relations. For the KinFaceW-II dataset, each relationship contains 250 pairs of kinship images.

There are 143 pairs of kinship images in the Cornell KinFace dataset,[6] where 40%, 22%, 13% and 26% are the F-S, F-D, M-S, and M-D relations, respectively.

There are 600 face images of 400 persons from 200 families in the UB KinFace dataset. For each family, there are three images, corresponding to the child, young parent and old parent, respectively. Since there are three images for each family, we constructed two subsets for the UB KinFace dataset: Set 1 (200 old parent and young parent image pairs) and Set 2 (200 young parent and child image pairs). Since there are large imbalances of the four kinship relations of the UB Kinface database (nearly 80% of them are father-son relations), we have not considered separate kinship relation verification on this dataset. Fig. 1 shows some example images with kinship relations of these datasets, respectively.

TABLE I

COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT METRIC LEARNING STRATEGIES ON THE KINFACEW-I DATASET

Method	F-S	F-D	M-S	M-D
SML (LBP)	63.7 (1)	64.2 (1)	58.4 (1)	64.4 (1)
SML (SPLE)	63.6 (1)	62.6 (1)	63.4 (1)	70.5 (1)
SML (SIFT)	65.5 (1)	61.5 (1)	63.0 (1)	65.5 (1)
CML	69.5 (1)	65.5 (1)	64.5 (1)	72.0 (0)
IML	70.5 (1)	67.5 (0)	65.5 (1)	72.0 (0)
DMML	**74.5**	**69.5**	**69.5**	**75.5**

TABLE II

COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT METRIC LEARNING STRATEGIES ON THE KINFACEW-II DATASET

Method	F-S	F-D	M-S	M-D
SML (LBP)	69.0 (1)	69.5 (1)	69.5 (1)	69.0 (1)
SML (SPLE)	71.3 (1)	72.0 (1)	75.5 (1)	76.0 (1)
SML (SIFT)	69.0 (1)	70.5 (1)	71.0 (1)	71.0 (1)
CML	73.5 (1)	73.0 (1)	76.0 (1)	76.5 (1)
IML	74.5 (1)	74.0 (0)	76.5 (0)	78.5 (0)
DMML	**78.5**	**76.5**	**78.5**	**79.5**

B. Experimental Setups

In our experiments, face images were aligned and cropped into 64×64 pixels according to the provided eyes positions in each dataset. We performed five-fold cross validation experiments on all the kinship datasets, where each subset of these datasets was equally divided into five folds so that each fold contains nearly the same number of face pairs with kinship relation. Specifically, for face images in each fold of these datasets, all pairs of face images with kinship relation were used as positive samples, and those without kinship relation as negative samples. Hence, the positive samples are the true pairs of face images (one from the parent and the other from the child), and the negative samples are false pairs of face images (one from the parent and the other from the child's image who is not his/her true child of the parent). Generally, the number of positive samples is much smaller than that of the negative samples. In our experiments, each parent face image was randomly combined with a child image who is not his/her true child of the parent to construct a negative pair. Moreover, each pair of parent and child images appeared once in the negative samples.

We tuned the parameters of our DMML method on the KinFaceW-II dataset because this dataset is the largest one and it is more effective to tune parameters on this dataset than others. We learned our DMML model on the first three folds of the KinFaceW-II dataset, and used the fourth fold to tune the parameters of DMML. In our implementations, the parameters r and λ were empirically set as 5 and 2, respectively. Having learned the DMML model, we apply it for kinship verification on all the four kinship datasets.

[5]http://www.cse.buffalo.edu/ yunfu/research/Kinface/Kinface.htm.

[6]While there are 150 pairs of parents and children images in [10], only 143 pairs were released for evaluation.

The SVM classifier with the RBF kernel was used for classification. It is to be noted that other classification methods such as the nearest neighbor (NN) and the k-nearest neighbor (KNN) classifier are also applicable to our kinship verification tasks. Our empirical results have also shown that SVM can obtain better performance than the other compared classifiers, which will be presented in the next subsections.

C. Results and Analysis

1) Comparison With Different Metric Learning Strategies: We first compare our method with three other different metric learning strategies:

- Single Metric Learning (SML): we learn a single distance metric by using the first term of (4) with each singe feature representation.
- Concatenated Metric Learning (CML): we first concatenate different features into a longer feature vector and then learn a single distance metric by using the first term of (4) with the augmented feature representation.
- Individual Metric Learning (IML): we learn the distance metric for each feature representation by using the first term of (4) and then use the equal weight to compute the similarity of two face images.

Tables I-IV show the mean verification rates of different metric learning strategies on different kinship datasets. To further investigate the performance differences between our DMML and the other compared methods, we evaluated the verification results by using the null hypothesis statistical test based on Bernoulli model [3] to check whether the differences between the results of our method and those of other methods are statistically significant. The results of the p-tests are given in the brackets right after the verification rate of each method in each table, where the number "1" represents significant

TABLE III
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT METRIC LEARNING STRATEGIES ON THE CORNELL KINFACE DATASET

Method	F-S	F-D	M-S	M-D
SML (LBP)	65.5 (1)	62.0 (1)	73.0 (1)	58.0 (1)
SML (SPLE)	71.5 (1)	65.5 (1)	74.0 (1)	62.0 (1)
SML (SIFT)	64.5 (1)	65.5 (1)	73.5 (1)	61.0 (1)
CML	72.0 (1)	67.0 (1)	74.0 (1)	63.0 (1)
IML	72.5 (1)	67.5 (0)	74.5 (1)	64.5 (1)
DMML	**76.0**	**70.5**	**77.5**	**71.0**

TABLE IV
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT METRIC LEARNING STRATEGIES ON THE UB KINFACE DATASET

Method	Set 1	Set 2
SML (LBP)	60.7 (1)	58.8 (1)
SML (SPLE)	60.9 (1)	61.0 (1)
SML (SIFT)	60.5 (1)	59.5 (1)
CML	65.5 (1)	63.5 (1)
IML	66.5 (1)	65.5 (1)
DMML	**74.5**	**70.0**

TABLE V
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT MULTI-METRIC LEARNING METHODS ON THE KINFACEW-I DATASET

Method	F-S	F-D	M-S	M-D
MCCA	69.0 (1)	63.5 (1)	64.3 (1)	70.5 (1)
MMFA	70.0 (1)	64.0 (1)	64.3 (1)	70.5 (1)
LDDM	72.5 (0)	66.0 (1)	65.8 (1)	71.7 (1)
DMMA	70.5 (1)	65.5 (1)	65.3 (1)	70.9 (1)
MNRML	72.5 (0)	66.5 (1)	66.2 (1)	72.0 (1)
DMML	**74.5**	**69.5**	**69.5**	**75.5**

TABLE VI
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT MULTI-METRIC LEARNING METHODS ON THE KINFACEW-II DATASET

Method	F-S	F-D	M-S	M-D
MCCA	74.0 (1)	72.1 (1)	74.8 (1)	75.3 (1)
MMFA	74.3 (1)	72.8 (1)	75.5 (1)	75.3 (1)
LDDM	74.8 (1)	73.6 (1)	76.5 (1)	76.2 (1)
DMMA	73.5 (1)	72.8 (1)	76.0 (0)	74.5 (1)
MNRML	76.9 (0)	74.3 (0)	77.4 (0)	77.6 (0)
DMML	**78.5**	**76.5**	**78.5**	**79.5**

TABLE VII
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT MULTI-METRIC LEARNING METHODS ON THE CORNELL KINFACE DATASET

Method	F-S	F-D	M-S	M-D
MCCA	71.5 (1)	65.8 (1)	73.5 (1)	63.5 (1)
MMFA	71.5 (1)	66.4 (1)	73.5 (1)	64.5 (1)
LDDM	73.0 (1)	66.9 (1)	74.5 (1)	67.5 (1)
DMMA	71.0 (1)	65.5 (1)	73.0 (1)	65.5 (1)
MNRML	74.5 (0)	68.8 (0)	77.2 (0)	65.8 (1)
DMML	**76.0**	**70.5**	**77.5**	**71.0**

TABLE VIII
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF DIFFERENT MULTI-METRIC LEARNING METHODS ON THE UB KINFACE DATASET

Method	Set 1	Set 2
MCCA	65.5 (1)	64.0 (1)
MMFA	65.0 (1)	64.0 (1)
LDDM	66.5 (1)	66.0 (1)
DMMA	65.5 (1)	63.5 (1)
MMNRML	66.5 (1)	65.5 (1)
DMML	**74.5**	**70.0**

difference and "0" represents otherwise. We see from these tables that our DMML outperforms the other compared metric learning strategies in terms of the mean verification rate.

2) Comparison With Existing Multi-Metric Learning Methods: We compared our DMML method with five existing multi-metric learning methods, including Multi-feature Canonical Correlation Analysis (MCCA) [29], Multi-feature Marginal Fisher Analysis (MMFA) [29], Local Discriminative Distance Metrics (LDDM) [25], Discriminative Multi-Manifold Analysis (DMMA) [21] and Multi-feature Neighborhood Repulsed Metric Learning (MNRML) [23]. Since LDDM and DMMA were originally developed for recognition tasks, we extended them for our kinship verification task by modifying their objectives, respectively. Specifically, we learn a local distance metric by LDDM or DMMA for each triplet which consists of one positive pair and one negative pair. Then, we combined these local distance metrics for verification by following the ensemble strategy in [25]. Tables V-VIII show the verification rate of these methods on different kinship datasets. As can be seen, our proposed DMML always outperforms the other compared methods in terms of the mean verification rate.

To better visualize the difference between our proposed DMML and the other compared multi-metric learning methods, the receiver operating characteristic (ROC) curves of different methods are shown in Fig 2. We see that the ROC curves of our DMML method are higher than those of other compared multi-metric learning methods.

3) Comparison With Different Classifiers: We investigated the performance of our DMML by using different classifiers. We compared SVM with another two widely used classifiers: NN and KNN. For KNN, the parameter k was empirically set as 31 in our experiments. Table IX tabulates the verification rate of our DMML method when different classifiers were used for kinship verification. We see that SVM always outperforms NN and KNN in terms of the verification accuracy in our kinship verification task.

4) Parameter Analysis: We evaluated the effect of the parameter r in DMML. Fig. 3 plots the verification accuracy of our DMML versus different number of r on different datasets. We see that our DMML method is in general robust to the varying value of r, and the best performance can be obtained when r was set as 5.

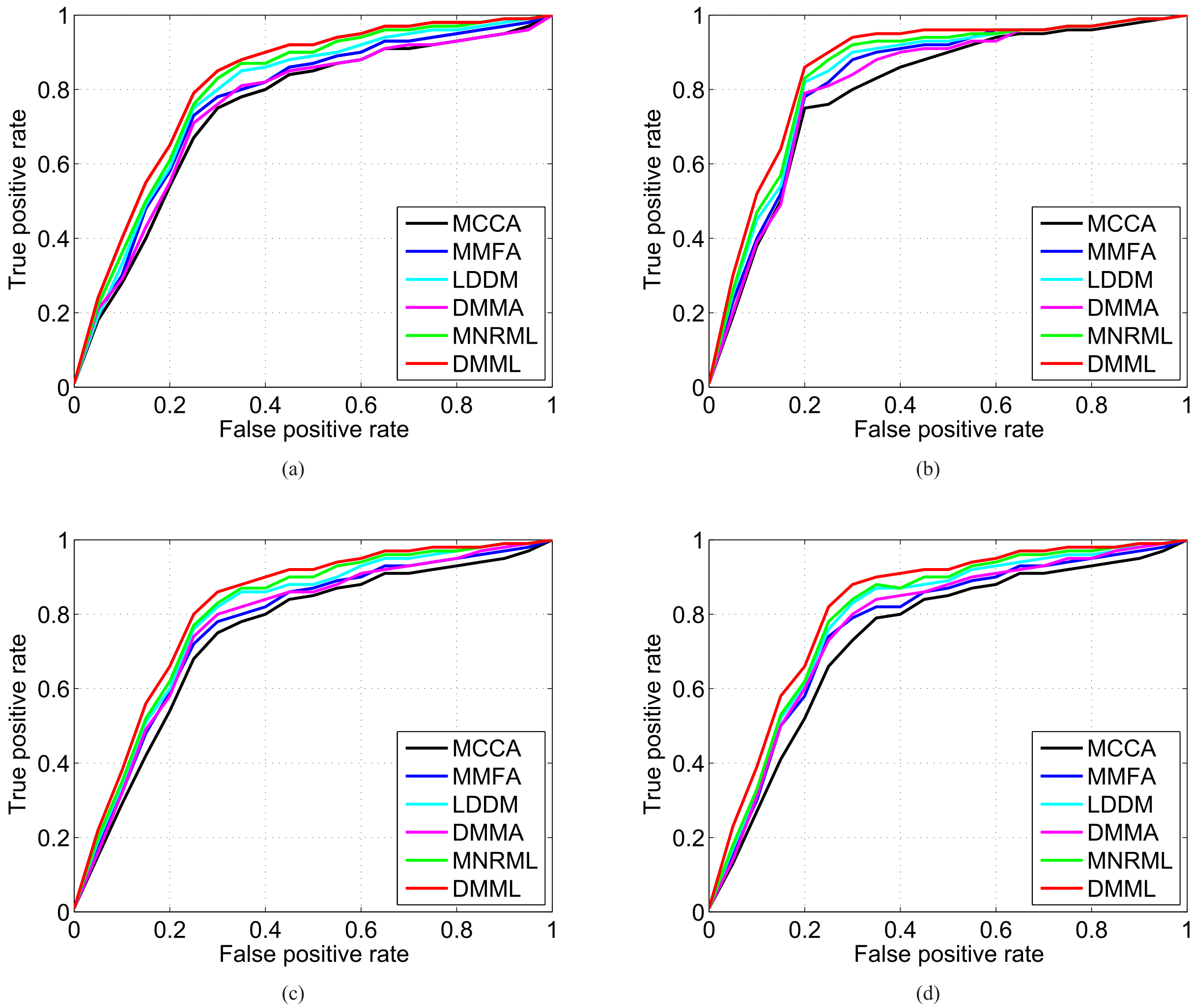

Fig. 2. The ROC curves of different methods obtained on the (a) KinFaceW-I, (b) KinFaceW-II, (c) Cornell KinFace, and (d) UB KinFace datasets, respectively.

TABLE IX

VERIFICATION ACCURACY (%) OF DIFFERENT CLASSIFIERS ON DIFFERENT KINSHIP DATASETS

Method	KinFaceW-I				KinFaceW-II				Cornell				UB	
	F-S	F-D	M-S	M-D	F-S	F-D	M-S	M-D	F-S	F-D	M-S	M-D	Set 1	Set 2
NN	71.0	67.0	67.0	73.0	74.0	72.5	75.5	77.0	72.5	67.0	74.5	67.0	69.5	67.0
KNN	73.0	67.5	68.0	74.0	76.5	74.5	78.0	78.5	74.5	69.0	76.0	69.0	73.5	68.5
SVM	**74.5**	**69.5**	**69.5**	**75.5**	**78.5**	**76.5**	**78.5**	**79.5**	**76.0**	**70.5**	**77.5**	**71.0**	**74.5**	**70.0**

Fig. 4 shows the verification rate of DMML versus different number of iterations on different datasets. We see that our proposed DMML converges to a local optimal peak in a few number of iterations.

Fig. 5 show the verification rate of DMML versus different number of feature dimension on different datasets. We see that our proposed DMML method obtains stable verification performance when the feature dimension is larger than 40.

5) Computational Time: Table X shows the time spent on the training and the testing (verification) phases by different multi-metric learning methods, where a 2.4-GHz CPU, a 6GB RAM, the Matlab software, the KinFaceW-I dataset, and the SVM classifier were used.

As can be seen from this figure, the computational complexity of our DMML and the existing MNRML for training are larger than other two because both of them are iterative methods. However, the recognition time of DMML is comparable to those of other multi-metric learning methods.

6) Comparisons With Human Observers in Kinship Verification: Lastly, we also tested human ability in kinship verification via facial image analysis. We randomly selected 100 pairs (50 positive and 50 negative) of face samples from each of the four subsets of the KinFaceW-I and KinFaceW-II datasets, and presented them to 10 human observers (5 males and 5 females) who are 20-30 years old. We didn't train them how to verify kinship relation from facial images. There are two parts in this experiment. For the first part, only

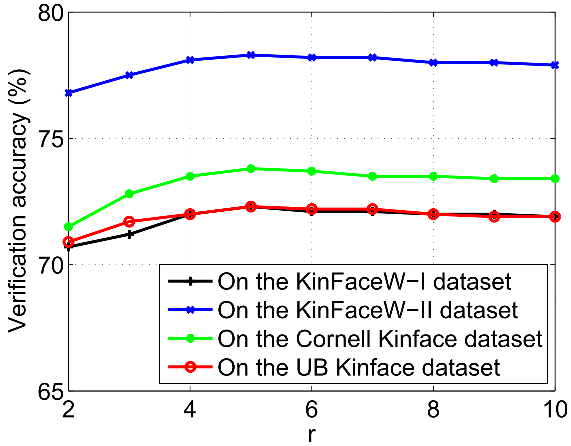

Fig. 3. Verification rate DMML versus different values of *r* on different kinship datasets.

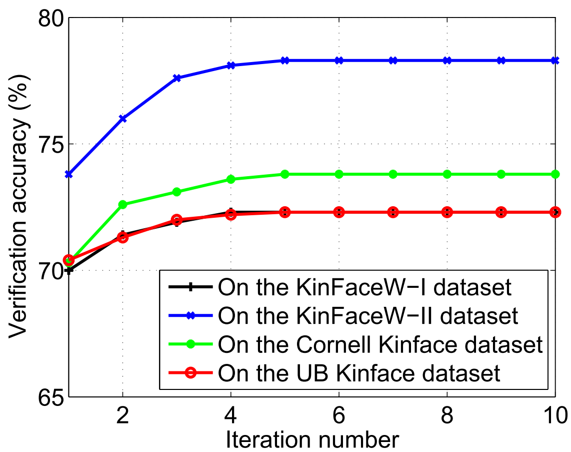

Fig. 4. Verification rate of DMML versus different number of iterations on different kinship datasets.

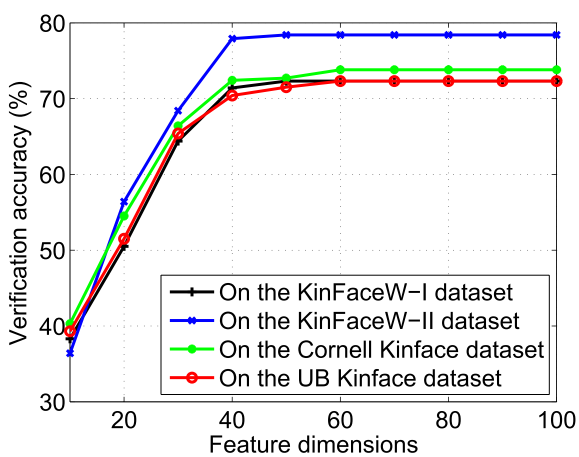

Fig. 5. Verification rate of our DMML versus different feature dimensions on different kinship datasets.

the cropped face regions such as the images are shown to human observers (HumanA). For the second part, the whole original color face images such as the samples are presented to human observers. Hence, HumanA aims to test kinship verification ability only from face part in the image, and HumanB intends to test the ability from multiple cues in the images such as face region, skin color, hair, and background. Therefore, face images provided in HumanA are the same as those used in this work. Tables XI shows the performance of these observers. We clearly see that our proposed DMML obtains better verification performance than HumanA, and is comparable to HumanB.

TABLE X
CPU TIME (IN SECOND) USED BY DIFFERENT MULTI-METRIC LEARNING METHODS ON THE KINFACEW-I DATASET

Method	Training	Testing
MCCA	0.05	5.55
MMFA	0.05	5.55
MNRML	25.50	5.55
DMML	26.50	5.55

TABLE XI
COMPARISON OF THE MEAN VERIFICATION RATE (%) OF HUMAN ABILITY ON KINSHIP VERIFICATION AND OUR PROPOSED DMML METHOD ON THE KINFACEW-I AND KINFACEW-II DATASETS

Method	KinFaceW-I				KinFaceW-II			
	F-S	F-D	M-S	M-D	F-S	F-D	M-S	M-D
HumanA	61.0	58.0	66.0	70.0	61.0	61.0	69.0	73.0
HumanB	67.0	65.0	75.0	77.0	70.0	68.0	78.0	80.0
Ours	**74.5**	**69.5**	**69.5**	**75.5**	**78.5**	**76.5**	**78.5**	**79.5**

D. Discussion

In this subsection, we discuss some potential applications of our kinship verification results presented in this work. One representative application of kinship verification is social media analysis. For example, there are tens of billion images in the popular Facebook website, and more than 2.5 billions images are added to the website each month. How to automatically organize such large-scale data remains a challenging problem in computer vision and multimedia. There are two key questions to be answered: 1) who these people are, and 2) what their relations are. Face recognition is an important approach to address the first question, and kinship verification is a useful technique to approach the second question. When kinship relations are known, it is possible to automatically create family trees from these social network websites. Currently, our method has achieved 70-75% verification rate when two face images were captured from different photos, and 75-80% verification rate from the same photo. While the performance is lower than the state-of-the-art face verification accuracy which is above 90% verification rate on the LFW dataset, it still provides useful information for us to analyze the relation of two persons because these numbers are not only much higher than random guess (50%), but also comparable to that of human observers.

Another important application of kinship verification is missing children search. Currently, DNA testing is the dominant approach to verify the kin relation of two persons, which is effective to find missing children. However, there are two limitations for the DNA testing: 1) the privacy of

DNA testing is very high, which may make it restricted in some applications; 2) the cost of DNA testing is higher. However, kinship verification from facial images can remedy these weaknesses because verifying kinship relations from facial images is very convenient and its cost is very low. For example, if we want to find a missing child from thousands of children, it is difficult to use the DNA testing to verify their kin relation due to privacy concerns. However, if our kinship verification method is used, we can quickly first identify some possible candidates which have high similarity from facial images, Then, the DNA testing is applied to get the exact search result. Different users may have different preferences to remove the false candidates. Hence, the ROC curve results in Fig. 4 can provide some guidelines for users in practical applications, which can provide a trade-off between the search accuracy and efficiency.

V. Conclusion and Future Work

We make the following four observations from the above experimental results:

- SPLE is the best feature descriptor for kinship verification from facial images. Different from other hand crafted feature representations methods such as LBP and LBP, the SPLE feature is directly learned from training samples and hence it is more data-adaptive and higher verification accuracy can be achieved.
- 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.
- 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.

For future work, we are interested in applying the proposed kinship verification approach in this work for the following potential applications:

- Social media mining: we will apply our proposed kinship verification approach for face image analysis in social network websites. Since the current verification rate is less than 80%, we will combine more cues such as texts and contextual information with face images to further improve the verification performance in social networks.
- Family alumni organization: we will employ our proposed kinship verification approach for family alumni photo organization. Since there are usually large age progression in face images in family alumni photo, we will combine both kinship verification and age-invariant face recognition techniques to further improve verification performance.

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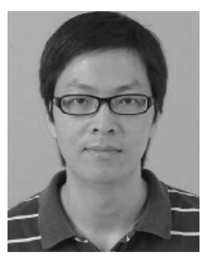

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