Graph-based Kinship Recognition

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1. Introduction

Image-based kinship recognition is an important problem in the reconstruction and analysis of social networks. Prior studies [2, 7, 5, 1] have focused solely on pairwise kinship verification, *i.e.* whether or not two people are kin. Such approaches fail to exploit the fact that many real-world photographs with multiple family members. For such case, the probability of two people being brothers increases when both people are recognized to have the same father. In this work [4], we propose to model the group kinship in a family photo in a manner of fully connected graph. It is motivated by the truth that in a family, the recognized kinship of a particular pair of faces provides evidence for (non)kinship between other pairs of people. For example, in a family, two siblings should have the same father and mother.[1] As a result, the group kinship recognition can be constrained and improved by a graph structure.

The general framework is illustrated in Figure 1. Pairwise facial features including appearance, gender and age are firstly considered to describe the kinship facial similarity. During the training phase, with the extracted features a multi-class classifier is trained to recognize different types of kinship (specifically 12 types as seen in Section 2.2). A valid kinship graph is defined as a fully connected graph with the vertices as the faces and the edges as the kinships. Using a few simple kinship rules, we can generate all valid kinship graphs with all pairwise connections. For each new test image, the predicted kinship graph is the one that obtains the highest score by summing up the scores of the pairwise classifiers that correspond to the edges. The graphs can benefit the group kinship recognition by encouraging valid kinship graph prediction. Because our graph-based algorithm shares information among the pairwise classifiers, ambiguities in the pairwise kinship classifications may be resolved, which may lead to improved performance. In addition, we introduce a database of group photographs with kinship annotations.

[1] In this study, step relationships are not considered.

2. Methodology

2.1. Feature Extraction

To enable the similarity comparison between faces, face alignment should be employed. The regression based facial landmarks alignment method [8] is applied in our work. The local binary pattern (LBP) [6] features extracted from each cell in a 7×5 grid [1] is used to model the facial appearance. The gender and age features estimated from the bio-inspired features (BIF) [3] is addition to the appearance descriptor. The final descriptive feature vector to model a pair of facial images (I_i, I_j) is organized as $\mathbf{x}_{ij} = [f_{\text{LBP}}(I_i), f_{\text{LBP}}(I_j), f_{\text{gender}}(I_i), f_{\text{gender}}(I_j), f_{\text{age}}(I_i, I_j)]$.

2.2. Pairwise Kinship Classification

In order to construct a kinship graph, it is necessary to define directional kinships which are enumerated as father→daughter (FD), father←daughter (DF), father→son (FS), father←son (SF), mother→daughter (MD), mother←daughter (DM), mother→son (MS), mother←son (SM), brother→sister (BS), brother←sister (SB), brother-brother (BB), and sister-sister (SS). More distant kinship relationships such as grandparents-grandchildren, cousins, and uncle/aunt-nephew/niece may also be inferred if the family picture also contains the "intermediate" people with these kinship types. A multi-class linear logistic regressor is trained by minimizing the penalized conditional log-likelihood $\mathcal{L}(\mathbf{W}, \mathbf{b}) = \underset{\mathbf{W}}{\operatorname{argmax}} \left(\sum_{(i,j)} \log p(\mathbf{y}_{ij}|\mathbf{x}_{ij}) - \lambda \|\mathbf{W}\|_2^2 \right)$, where $p(\mathbf{y}|\mathbf{x}) = \frac{\exp(\mathbf{y}^\top(\mathbf{W}^\top\mathbf{x}+\mathbf{b}))}{\sum_{\mathbf{y}'} \exp(\mathbf{y}'^\top(\mathbf{W}^\top\mathbf{x}+\mathbf{b}))}$. For a pair of face images, the predicted kinship is thus given by $\mathbf{y}^* = \underset{\mathbf{y}}{\operatorname{argmax}}\, \mathbf{y}^\top \left(\mathbf{W}^\top\mathbf{x} + \mathbf{b}\right)$.

2.3. Fully Connected Kinship Graphs

A fully connected kinship graph can be formulated as $G = (V, E)$ in which faces correspond to vertices and edges to kinships. It is noted that all pairwise connections are considered. The kinship graphs are pre-defined accord-

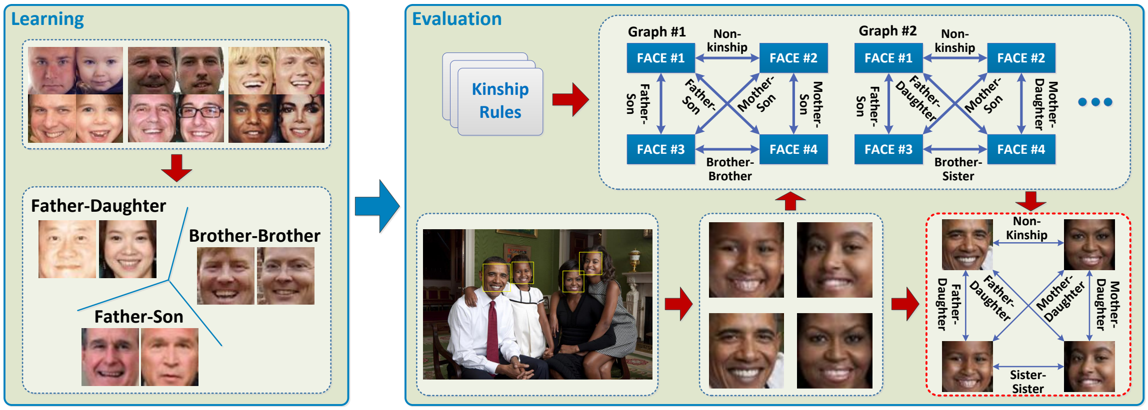

Figure 1. Overview of the proposed kinship recognition system.

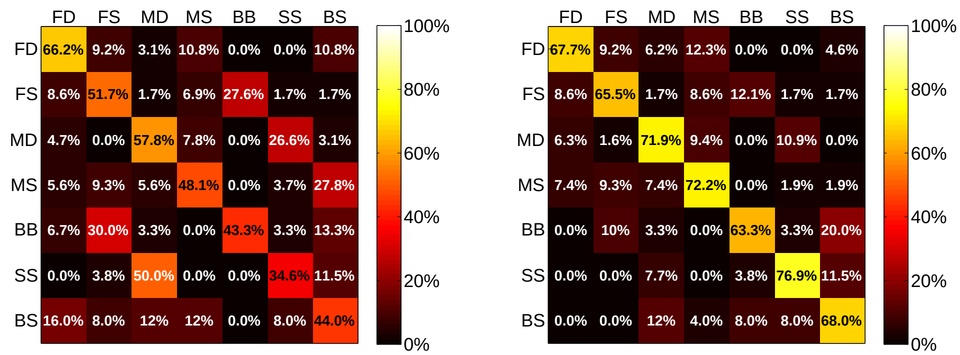

Figure 2. Confusion matrices for the pairwise and graph-based approaches.

ing to some constraints which are some logical semantics like: if A and B are brothers and C is the father of A, then C must also be the father of B. For a particular graph, a score is defined as the summation of the kinship classifier scores that correspond to each of the edges in the graph $s(G|\mathcal{I}) = \sum_{(i,j)\in E} \mathbf{y}_{ij}^\top \left(\mathbf{W}^\top \mathbf{x}_{ij} + \mathbf{b}\right)$. We perform kinship estimation by maximizing the score over the whole set of candidate kinship graphs $G^* = \underset{G\in\mathscr{G}}{\operatorname{argmax}}\, s(G|\mathcal{I})$. In other words, the predicted optimal kinship graph is the one with the highest score.

3. Experiment Results and Discussions

We have constructed a new database that contains more than 200 image pairs for each of three possible sibling relations [4]. All the faces have been aligned according to the position of eyes, and resized to a common size of 64×64 pixels. In our experiments, the KFW-II and Sibling-Face databases are combined and used for training. We employ the family photos in our Group-Face database as the test set. The results shown in Fig. 2 suggest that the proposed method outperforms the pure pairwise kinship recognizer. Especially, the fully connected graph approach is able to recover from errors from the age/gender estimations.

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