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Understanding and Verifying Kin Relationships in a Photo

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ABSTRACT
There is an urgent need to organize and manage images of people automatically due to the recent explosion of such data on the Web in general and in social media in particular. Beyond face detection and face recognition, which have been extensively studied over the past decade, perhaps the most interesting aspect related to human-centered images is the relationship of people in the image. In this work, we focus on a novel solution to the latter problem, in particular the kin relationships. To this end, we constructed two databases: the first one named UB KinFace Ver2.0, which consists of images of children, their young parents and old parents, and the second one named FamilyFace. Next, we develop a transfer subspace learning based algorithm in order to reduce the significant differences in the appearance distributions between children and old parent's facial images. Moreover, by exploring the semantic relevance of the associated metadata, we propose an algorithm to predict the most likely kin relationships embedded in an image. In addition, human subjects are used in a baseline study on both databases. Experimental results have shown that the proposed algorithms can effectively annotate the kin relationships among people in an image and semantic context can further improve the accuracy.
Keywords: Context, face recognition, feature extraction, inheritance, kinship verification

I. INTRODUCTION

Kin relationships are traditionally defined as ties based on blood and marriage. They include lineal generational bonds (children, parents, grandparents, and great-grandparents), collateral bonds (siblings, cousins, nieces and nephews, and aunts and uncles), and ties with in-laws. An often-made distinction is that between primary kin (members of the families of origin and procreation) and secondary kin (other family members). The former are what people generally refer to as "immediate family," and the latter are generally labeled "extended family." Marriage, as a principle of kinship, differs from blood in that it can be terminated. Given the potential for marital break-up, blood is recognized as the more important principle of kinship.With the development of technology in modern multimedia society, image acquisition and storage by digital devices have never been easier than today. Storage unit like GB or TB is not qualified already in storing images from the Internet. For example, as the most popular social network website around the world, Facebook has already hosted over 20 billion images, with more than 2.5 billion new photos being added each month [1]. However, how to successfully and automatically manage the substantial images captured by people is a real challenge since it pushes the computer to its limit of image understanding-it requires both large-scale data analysis and high accuracy. In most cases, people are the focus of images taken by consumers and managing or organizing them essentially raises two problems: 1) who these people are and 2) what their relationships are. Establishing kinship using images can be utilized as context information in different applications including face recognition. However, the process of automatically detecting kinship in facial images is a challenging and relatively less explored task. The reason for this includes limited availability of datasets as well as the inherent variations amongst kins.

II. CONTRIBUTIONS OF THIS PAPER

This paper presents a kinship classification algorithm that uses the local description of the preprocessed Weber face image. To this end, we constructed two databases: the first one named UB KinFace Ver2.0, which consists of images of children, their young parents and old parents, and the second one named FamilyFace. Next, we develop a transfer subspace learning based algorithm in order to reduce the significant differences in the appearance distributions between children and old parent's facial images. The proposed algorithm outperforms an existing algorithm and yields a classification accuracy of 75.2%.we considers the kinship verification problem through face images. Genetics studies show resembling regions on faces among immediate family members are mostly concentrated on eyes, nose, mouth, etc. This motivates us the following research. First, we construct low-level features based on the hierarchical local regions. Second, an attribute based method is proposed towards meaningful middle-level representations for face images.

III. PROPOSED APPROACH

3.1 UB KinFace Database

To the best of our knowledge, the “UB KinFace Ver1.0”[2] is the first database containing images of both children and their parents at different ages. All images in the database are real world collections of public figures (celebrities and politicians) from the Web. We use a person’s name as the query for image search. The database used in this paper, named “UB KinFace Ver2.0” [3], is an extension of “UB KinFace Ver1.0” by considering more instances and ethnicity group impacts. A general view of this database is summarized in Fig. 1. Similar to “Labeled Faces in the Wild”[4] , these unconstrained facial images show a large range of variations, including pose, lighting, expression, age, gender, background, race, color saturation, and image quality, etc. The key difference between our database and that in [5] lies in our inclusion of young parents. Basically, our database comprises 600 images of 400 people which can be separated into 200 groups. Each group is composed of child, young–parent and old–parent images. The “UB KinFace Ver2.0” can be mainly divided into two parts in terms of race, i.e., Asian and non-Asian, each of which consists of 100 groups, 200 people and 300 images. Typically, there are four kin relations, i.e., “son–father,” “son–mother,” “daughter–father,” and “daughter–mother,” as shown in Fig. 1. As we can see, male celebrities of both Asian and non-Asian, either son or father, are dominant in the UB KinFace database. When four possible kin relations are considered in our problem, “fathers” reasonably become the essential roles, with 46.5% and 38.5% over all groups in “son–father” and “daughter–father” relations. This phenomenon can be explained by the fact that there are statistically more notable males than females in current government, entertainment and sports communities. Contexts and semantics in family albums are other factors that we can leverage to improve the accuracy. To this end, a new database called FamilyFace is built, which, including 214 images, 507 persons in total, is collected from the popular social network websites, e.g., Facebook and Flickr. The example images are shown in Fig. 2. In this database, there are kinship and other relationships, e.g., friendship and colleague, in each image, and they may coexist in the same image. In addition, not only Asian but also western people are considered in the database. Since we downloaded them from the Web and they are not subject to any specific constraints, these images may reveal real-world conditions for practical evaluations.

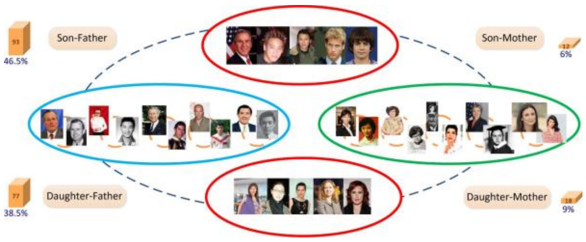

Fig. 1. KinFace database illustrations. Four groups of people and the corresponding four possible relationships: son–father, son–mother, daughter–father, and daughter–mother. Children images are in the red ellipse; male parents images are in the blue ellipse; female parents images are in the green ellipse (in online version).

Fig. 2. Sample images (top) from the FamilyFace database. The cropped faces contained in these images are shown in the second row.

3.2. Feature Extraction

Two typical features that can distinguish true child–parent pairs from the false ones are explored in this section. One is based on appearance and extracted by Gabor[6] filters (eight directions and five scales). Particularly, we first partition each face into regions in five layers, as illustrated in Fig. 3. As we can see, the entire face is the first layer. The second layer includes upper, lower, left, right and center parts of the face. The forehead, eyes, nose, mouth, and cheek areas constitute the third layer and their finer sub-regions form the fourth layer. A group of sub-regions based on the four fiducial points finally form the fifth layer. Then we impose Gabor filters on each local region. Similar idea has been adopted in [7] to analyze facial expressions through local features. Intuitively, kinship verification is also a process on local regions. For instance, when people are talking about kinship, they often compare regions on faces between children and their parents and wonder whether they share similar eyes, noses, or mouths. Another feature is based on the anthropometric model [8] which essentially considers structure information of faces. Based on the captured key points, we obtain 6-D structure features of ratios of typical region distances, e.g., “eye–eye” distance versus “eye–nose” distance. Structured information is believed to inherit largely from parents, and therefore might be promising for kinship verification. However, due to aging process [9], the old parents face structures are deformed from the ones when they were young. So, we use transfer subspace learning to mitigate this degrading factor. Since images obtained from the Web are under arbitrary environment, we first take advantage of “total variation” to remove lighting effects. Total variation, as first used in image denoising, has been successfully applied to illumination free face recognition [10]. After removing the lighting effect, we partition faces according to key points, i.e., the locations of left eye, right eye, nose tip, and the center of the mouth, into regions with different widths and heights Fig. 3. Face partitions in different layers and face image illumination normalization. For simplicity, only four layers are illustrated instead of five. Red dots on faces in Layer1 illustrate four key points mentioned in this paper (in online version). Nose tip and the center of the mouth, into regions with different widths and heights, as shown in Fig. 3.

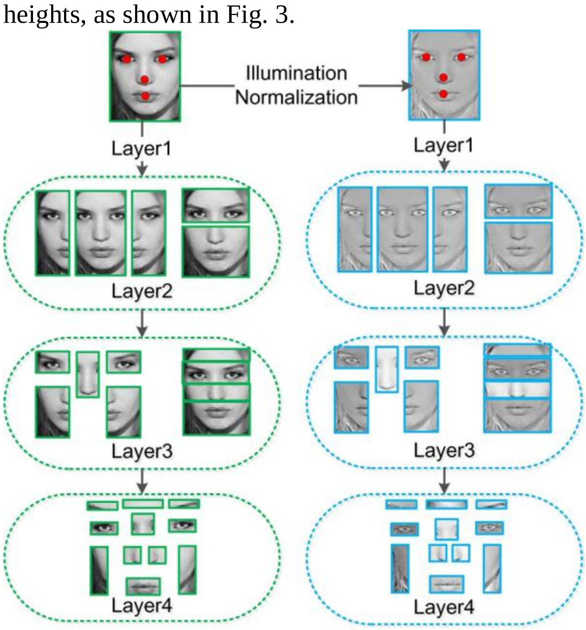

Fig.3. Face partitions in different layers and face image illumination normalization. For simplicity, only four layers are illustrated instead of five. Red dotson faces in Layer1 illustrate four key points mentioned in this paper (in online version).

3.3 .Face Detection and Weber Normalization

Since the objective of this research is to determine kinship in real world unconstrained images, preprocessing is an important component. The face region present in the image is first extracted using the Adaboost face detector . Figure 4 shows examples of detected face images. The illumination variation in detected face images is normalized using Weber's law based normalization technique. The goal of this algorithm is to remove the illumination factor and represent each image by its reflectance only, thus making it illumination invariant. The algorithm is briefly explained in "Weber Normalization" and Figure 4 shows examples of Weber normalized face.

Algorithm 1: Weber Normalization

Data: Face image
Output: Weber face image
Smoothen the image using a gaussian filter
F = F ⋆ G(x, y, _)
foreach *pixel in the image* **do**
Sum = _(pixelIntensity − neighborvalues);
V alue = arctan(V alue/pixelIntensity) ;
Assign value to the pixel in Weber Face Image
end

Fig.4. Weber normalized face images.

3.4.Transfer Subspace Learning

In our framework, we attempt to find a subspace where distribution similarity of two different data sets, i.e., child–old parent and child–young parent pairs, is maximized while in the subspace they still can be well separated in terms of kinship verification. Essentially, our approach is different from [11] in that ours takes advantage of the intermediate set (young parents) and prevents the failure of transfer. Moreover, instead of directly modeling three distributions similar to [12], we use two distributions by pairwise differences of three data sets, which leads to a simple but efficient model. In terms of transfer learning [13], method in [12] considers children, young parents and old parents as the source, intermediate and target domain, respectively. However, the differences of features between children and parents are more discriminative when we conduct two-class classification. So in this paper, we impose transfer learning on child–old parent and child–young parent pairs and therefore they become the source and target domain of the new problem. Our objective can be formulated as, finding an appropriate subspace where the low-dimensional representation of child–young parent feature difference and that of child–old parent are still discriminative and share the same distribution.

IV. EXPERIMENTS

Before following experiments, we conduct face and fiducial points detection on all images to obtain cropped face images. Then we align faces according to corresponding points using an affine transform. For the whole face and its small regions in each image, we crop them to fixed sizes. A few image preprocessing techniques, e.g., histogram equalization, are implemented to mitigate irrelevant factors

4.1. Verification on UB KinFace database

UB KinFace database 1 comprises 600 images which can be separated into 200 groups. Each group is composed of child, young-parent and old-parent images. Here we only use child and old-parent images. For the purpose of training and testing, we use 200 true child old parent pairs and 200 false child-old parent pairs with five-fold cross validation where 40 positive sample pairs 1UB KinFace Ver2.0 (for non-commercial purpose) is available and 40 negative sample pairs are used as test set at each round. Particularly, the positive samples are the true child-parent pairs while negative ones are children with randomly selected parents who are not their true parents. First, a kinship classification experiment is performed. Here in terms of biometrics, classification means finding a proper identity for the query. Specifically, in this section, our aim is that given a child's facial image, we will seek and return his/her parent's image, either young or old.

4.2. Experiments on different kinship relations

Typically, there are four kin relationships, i.e."son-father", "son-mother", "daughter-father" and "daughter-mother". To further explore the impact of the four kin relationships on verification accuracies, we collect 200 groups of family photos from a variety of online sources, e.g., Google Images and Flickr.

We select 90 groups of son and parent, and 90 groups of daughter and parent, respectively. In what follows, the entire UB KinFace is used for training while 90 true and 90 false child-parent pairs are used for testing. Given a pair of images, we first detect faces and extract features. Then binary attributes and relative attributes are obtained. Experimental results are shown in Table 1. In Table 1, verification accuracies on "daughter father" and "son-mother" are higher than "daughter mother" and "son-father". It suggests gender indeed affects the determination of kinship to some extent.

Table 1.Verification comparisons on four kin relations. The results are represented by True Positive (False Positive).

	Son V.S. Father	Son V.S. Mother
Son	68:89%(56:67%)	74:44%(57:78%)
Daughter	87:78%(55:56%)	61:11%(41:11%)

Attributes on different kinship relations: Although we already study different verification accuracies on four kin relations, it is interesting to consider which attribute is more hereditary. To this end, we calculate the amount of the same attributes in each kin relation. If father has arched eyebrows or high cheekbones, there is higher chance that his son has the same attribute. On the other hand, bushy eyebrows are discriminative for the mother-daughter relation. Compared with daughter, son has a high possibility to inherit narrow eyes and oval face from his parents.

V.CONCLUSION

In this paper, we study the kinship verification problem through face images. We investigate the problem of kinship verification through face images as well as the impact of contexts and semantics. First, the UB KinFace Ver2.0 was collected from the Web. Second, we propose a transfer subspace learning method using young parents as an intermediate set whose distribution is close to both the source and target sets. Through this learning process, the large similarity gap between distributions is reduced and child–old parent verification problem becomes more tractable. Third, we combine the proposed transfer learning approach with contextual information in family albums to further improve verification accuracy. Experimental results demonstrate our hypothesis on the role of young parents is valid and transfer learning can take advantage of it to enhance the verification accuracy. In addition, we prove that contextual information can reasonably improve the kinship verification accuracy via tests on the FamilyFace database.

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