Self-Similarity Representation of Weber Faces for Kinship Classification

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Abstract

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. This paper presents a kinship classification algorithm that uses the local description of the pre-processed Weber face image. A kinship database is also prepared that contains images pertaining to 272 kin pairs. The database includes images of celebrities (and their kins) and has four ethnicity groups and seven kinship groups. The proposed algorithm outperforms an existing algorithm and yields a classification accuracy of 75.2%.

1. Introduction

With the advent of multimedia age, digital images have become the new identity marker of a person. Online photo sharing has gained a lot of popularity and services such as Facebook, Flickr, and Picasa have a massive collection of digital images. Almost every user uploads and manages their photographs on one of these websites; Facebook alone has more than 100 billion images uploaded by summer 2011. At an average, each user has 282 photos uploaded on one (or more) of these sites. These websites are attempting to automatically organize the photographs in different ways such as performing automatic face recognition for name tagging, analyzing the content to determine the location or event, and analyzing faces to determine the relationship and sorting the photographs accordingly. Detecting relationships amongst images helps in understanding the context of the image. This can also be used as *soft* information for improving the accuracy of a face recognition algorithm. For example, in law enforcement applications, kinship can be used to establish the identities of the kins of a probe image.

In kinship classification, it is hypothesized that there is some similarity between two kins. For instance, kins can have similar eyes, nose shape, and forehead. However, both the extent and point of similarities vary from person to person which makes it difficult to establish kinship using face images only. Some of the kinship relations[1] such as father-daughter and mother-son have significant age differences thereby increasing the intra-class variations. Further, persons who look-alike but are not related (kins) can lead to lower inter-class variations. The problem is further exacerbated due to variations in pose, illumination, and expression. Figure 1 shows examples for some of these cases mentioned above and illustrates the challenge of kinship classification.

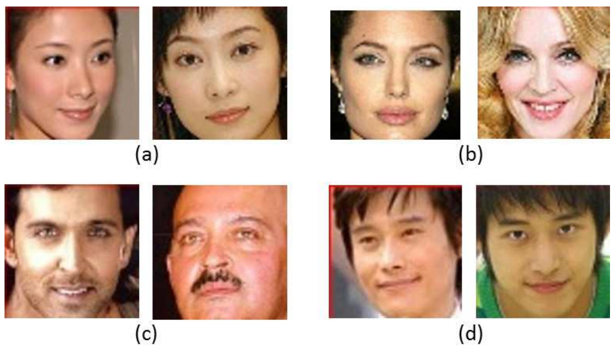

Figure 1. Illustrating inter and intra class variations in kinship classification: (a) similar looking kins, (b) different looking non-kins, (c) different looking kins (father-son), and (d) similar looking non-kins.

1.1. Literature Review

Kinship classification involves determining similarity in faces across age variations. Owing to the unique biological development and environmental factors that determine the appearance of every person, it is very challenging to define the relationship based on the appearance of kins. The research in kinship classification has recently received attention and is still in nascent stages.

[1]We have considered direct blood relationships only and divided kinship into seven subclasses - daughter-father, daughter-mother, son-father, son-mother, sister-sister, brother-brother, and brother-sister.

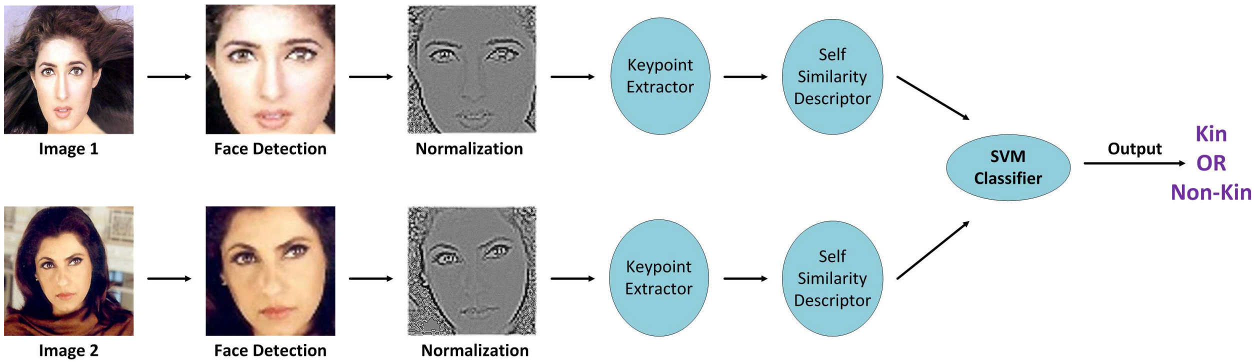

Figure 2. Illustrating the steps involved in the proposed kinship classification algorithm.

Fang et al. [5] utilized local information of faces for kinship recognition. They localized key parts of the face and extracted facial features such as skin color, gray value, histogram of gradient, and facial structure information. K-Nearest-Neighbor (KNN) and Support Vector Machine (SVM) were used to classify faces and an accuracy of 70.67% and 68.60% were obtained respectively on a database of 150 positive and 150 negative pairs. Xia et al. [14] used appearance and anthropometric models, proposed by Ramanathan and Chellappa [9], to determine the measurements and proportions of human faces. An accuracy of 56.67% was achieved by K-NN classification for classifying 90 positive and 90 negative kin pairs. They observed that kinship verification is more accurate for images of parents of younger age than with respect to images of parents of older age.

Xia et al. [14, 15] also presented kinship verification using transfer learning. For this, UB kinship database with three different sets was collected namely child (source), young parents (intermediate) and old (target) parent sets. They used transfer learning approach on children-young parents and young parents-old parents. An accuracy of 60% was achieved using K-NN. In different experiments, the authors validated the hypothesis that the role of images of younger parents is important and transfer learning improves the results.

Zhou et al. [16] evaluated the performance of kinship verification in an uncontrolled environment. A spatial pyramid learning-based (SPLE) feature descriptor was used for face representation. They calculated a vector for each pixel comprising of $r \times 8$ pixels on a radius r. This vector was normalized and for each image such vectors were clustered using K-Means and then a SVM classifier was trained. The authors reported an accuracy of 67.75% which was comparatively better than Local Binary Pattern (LBP) [1], Histogram of Gradients (HOG) [4], Principal Component Analysis (PCA) [8], and Linear Embedding (LE) [2]. Guo and Wang [6] extracted facial features in terms of face, mouth and nose and applied the DAISY descriptor for feature extraction. On a database of 100 kin and 100 non-kin pairs, an overall accuracy of 75% was achieved with Bayesian classifier.

1.2. Research Contributions

This research aims to develop a kinship classification algorithm that determines whether a pair of images belongs to class *kin* or *non-kin*. The major contributions of this research are summarized below:

1. Designed an algorithm for kinship classification. The proposed Self Similarity Representation of Weber face (SSRW) algorithm classifies a given pair into *kin* or *non-kin* class. The performance of the algorithm is also compared with one existing kinship classification algorithm [16].

2. Prepared a kinship database of 272 pairs. The database is also annotated with respect to the particular kinship relation, ethnicity, and gender.

2. Proposed SSRW Algorithm

Figure 2 illustrates the steps involved in the proposed SSRW kinship classification algorithm. There are four main steps in the algorithm: face detection, preprocessing, feature extraction, and classification.

Figure 3. Face images detected using the Adaboost face detector.

Figure 4. Weber normalized face images.

2.1. 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 [12]. Figure 3 shows examples of detected face images.

The illumination variation in detected face images is normalized using Weber's law based normalization technique [3, 13]. 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 faces.

Algorithm 1: Weber Normalization

Data: Face image
Output: Weber face image
Smoothen the image using a gaussian filter
$F = F * G(x, y, \sigma)$
foreach *pixel in the image* **do**
  $Sum = \Sigma(pixelIntensity - neighborvalues)$;
  $Value = \arctan(Value/pixelIntensity)$;
  Assign value to the pixel in Weber Face Image
end

2.2. Key-point Detection

After preprocessing, the next step is extracting salient points from the image around which the features can be extracted. It is important that these keypoints are invariant to scale transformations and are more discriminatory than normal pixels. Therefore, Difference of Gaussian (DoG) approach [7] has been applied to extract these features using the steps below.

1. Create a Gaussian subspace of the image by scaling and filtering it with a gaussian kernel.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

where * is a convolution operation and G is defined as

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (2)$$

2. Key points are detected by taking the *Differences of Gaussians* in the Gaussian subspace. It is to be noted that Laplacian of Gaussian can also be applied instead of *Differences of Gaussians* but they are more sensitive to noise.

$$G(x, y, k\sigma) - G(x, y, \sigma) \approx (k-1)\sigma^2 \nabla^2 G \quad (3)$$

3. The key points are extracted by taking the local extremas of the above difference of Gaussians.

4. Process of elimination via threshold centering and gradient detection is performed to retain only the discriminatory points.

2.3. Self-Similarity Descriptor and Classification

It is hypothesized that there is a certain amount of similarity in the texture and facial features of kins. To encode this similarity, a self-similarity descriptor (SSD), originally proposed by Shechtman and Irani [10], is used in this context. SSD computes the local self similarity cues in an image which is invariant to scale, translation and rotation. Algorithm 2 presents the steps involved in SSD.

The SSD is computed for matching pair of keypoints and the polar histograms of each keypoint obtained using Algorithm 2 are then matched using χ^2 distance measure. The χ^2 distance measures (in a vector form) are provided as input to the SVM classifier [11] with the classes being *kin* and *non-kin*.

3. Performance Evaluation

To evaluate the performance of the proposed kinship classification algorithm, we have collected a database of face images with kins and non-kins. The performance of the algorithm is also evaluated on the UB kinship database [14, 15] and compared with one existing kinship classification algorithm. As mentioned previously, Zhou et al. [16] propose a kinship classification algorithm based on a Spatial Pyramid Learning descriptor (SPLE). The feature vector is computed by taking the neighboring pixel values into account and a 1D feature vector is created by combining all the LE Descriptors [2] obtained in the spatial domain. The descriptor for each image is calculated and the Normalized Absolute Histogram Descriptor (NAHD) is computed between a pair of images. NAHD is provided as input to SVM with Radial Basis Function (RBF) kernel for classification.

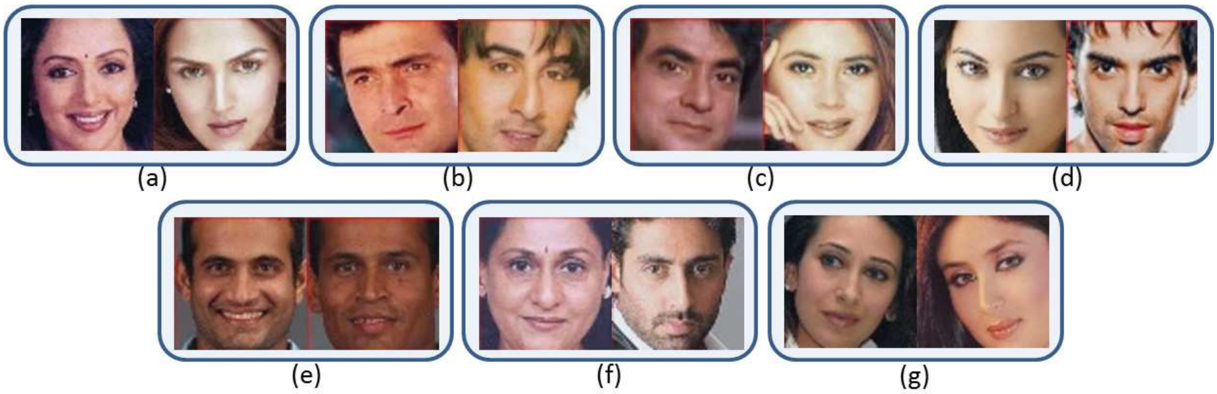

Figure 5. Sample images from the IIITD kinship database illustrating different kinship relations: a) mother-daughter, b) father-son, c) father-daughter, d) sister-brother, e) brother-brother, f) mother-son, and g) sister-sister.

Algorithm 2: Self Similarity Algorithm

Data: Face Image
Output: Self-Similarity Feature Vectors
foreach *keypoint (pixel) in the image* **do**
  $patch1 = 5 \times 5$ image patch with pixel in center;
  $patch2 = 40 \times 40$ image patch with pixel in center;
  SSD = Sum of squared differences between overlapping windows of $patch1$ and $patch2$;

$$DS_q(x, y) = \exp\left(\frac{-SSD_q(x, y)}{max(var_{noise}, var_{auto(q)})}\right) \quad (4)$$

  where DS is the surface distance, var_{noise} is a constant for illumination, and var_{auto} is the maximal variance of difference of small patches around the pixel;
  Transform DS into log-polar bins using 4 radius and 20 angles;
  Take maximal intensity in each bin as the bin descriptor value;
  These 80 values are the feature vector for that pixel;
end

3.1. IIITD Kinship Database

The authors have prepared the *IIITD Kinship Database*[2] comprising 544 images of 272 pairs in unconstrained environment. The database consists of celebrities images downloaded from the internet. The images have been annotated with respect to the kinship relation and ethnicity of the individuals. The database is also augmented with 272 non-kin pairs. The images have been classified into four different ethnicities: Afro-American, American, Indian, and Asian except Indian. The kinship relation has been categorized into the following seven relations: Brother - Brother, Brother - Sister, Father - Daughter, Father - Son, Mother - Daughter, Mother - Son, and Sister - Sister. Figure 5 shows sample images from the IIITD kinship database and Figures 6 and 7 show the distribution of ethnicity and kinship relations in the IIITD kinship database.

[2]The database will be released to the research community on a request basis.

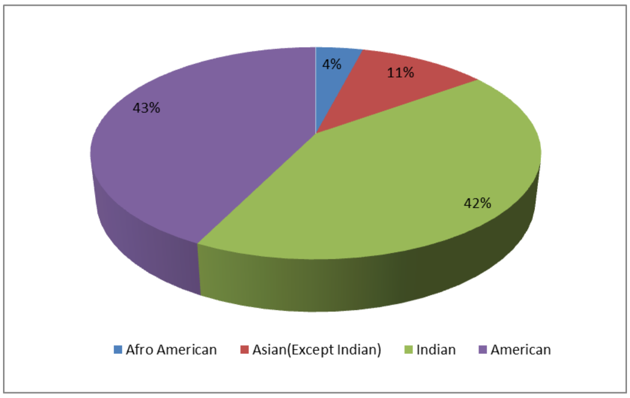

Figure 6. Ethnicity distribution in the IIITD kinship database.

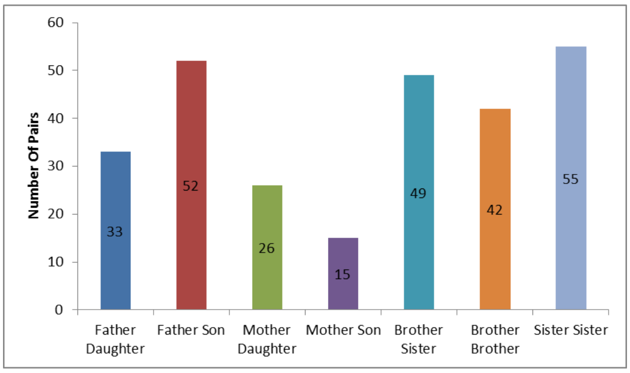

Figure 7. Distribution of different relations in the IIITD kinship database (kin pairs only).

3.2. Experiment Protocol

The proposed SSRW and existing SPLE kinship classification algorithms are evaluated on the IIITD kinship database and the publicly available UB Kinship database [14, 15]. UB database comprises images pertaining to 200 kin-pairs (600 images of 400 people which are separated into 200 groups and each group is composed of child, young parent, and old-parent images). Unlike the IIITD kinship database, the UB database has images pertaining to only four kinship classes: son-father, son-mother, daughter-father, and daughter-mother. The results are computed with five-fold cross validation and average classification accuracies are reported.

3.3. Results and Analysis

Figures 8 and 9 summarize the results of the proposed and existing algorithms on the IIITD kinship database. The key observations and analysis are as follows:

- To determine the best kernel and its parameters, experiments are performed with different kernels of SVM. As shown in Table 1, linear kernel with cost parameter = 1 yields 74.1% accuracy with standard deviation = 2.27 whereas the radial basis function (RBF) kernel with parameter $c = 10$ and $\gamma = 0.1$ yields comparatively higher accuracy of 75.2% but the standard deviation is 4.91%.

- The proposed algorithm yields an average classification accuracy of 75.2% and the algorithm by Zhou et al. [16] yields an average accuracy of 57.5% on the IIITD kinship database.

- As mentioned earlier, the IIITD kinship database is annotated with respect to four ethnicity and seven kinship classes. Therefore, it is possible to analyze the results across different ethnicity and kinship classes. Figure 8 shows the results of both the algorithms on different ethnicity classes and Figure 9 shows the results on different kinship classes. These results clearly indicate that the proposed algorithm is noticeably (at least 28%) better than existing SPLE algorithm on both the groups.

- Since, 85% of the images belong to Indian and American ethnicity, higher accuracies are observed for this group. It is also observed that the same gender kinship groups yield higher classification accuracy than different gender kinship groups.

- On the UB kinship database, out of 200 pairs, only 175 pairs are used in the experiments because the Adaboost face detector fails to detect some faces. As shown in Table 2, the proposed algorithm yields an accuracy of 52.5% on the child vs older parents group and 55.3% on child vs young parents group. On further analyzing the results, it is observed that low accuracy on these sets is attributed to low detection of key points on the Weber faces of these images. On this database also, the proposed algorithm outperforms SPLE algorithm by at least 4.1%.

- As shown in Figure 10, there are some cases when both the algorithms provide correct results and some cases when either one of them or both fail. In our opinion, the proposed algorithm fails to perform when there is large intra class variations due to age variations.

Kernels	Accuracy and Std. Deviation
Linear with cost = 1	74.1 ± 2.27
Linear with cost = 10	69.2 ± 3.54
Linear with cost = 100	69.2 ± 4.46
Polynomial Degree = 1	70.1 ± 6.82
Polynomial Degree = 2	72.8 ± 4.64
Polynomial Degree = 3	71.1 ± 4.00
RBF $c = 1, \gamma = 0.1$	73.8 ± 6.31
RBF $c = 10, \gamma = 0.1$	75.2 ± 4.91
RBF $c = 100, \gamma = 0.1$	70.3 ± 4.75
RBF $c = 1, \gamma = 1$	74.5 ± 2.99
RBF $c = 10, \gamma = 1$	71.0 ± 7.14
RBF $c = 100, \gamma = 1$	66.6 ± 3.59
RBF $c = 1, \gamma = 5$	67.2 ± 6.36
RBF $c = 10, \gamma = 5$	66.3 ± 4.03
RBF $c = 100, \gamma = 5$	64.2 ± 6.80

Table 1. Classification accuracy of SVM classifier with different kernels and parameters.

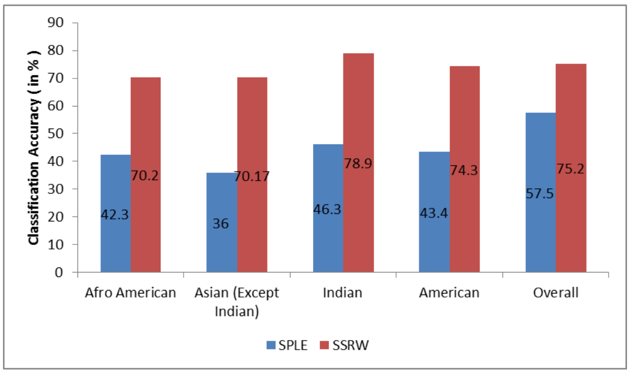

Figure 8. Classification results of the proposed SSRW and existing SPLE algorithms for different ethnicity variations on the IIITD kinship database.

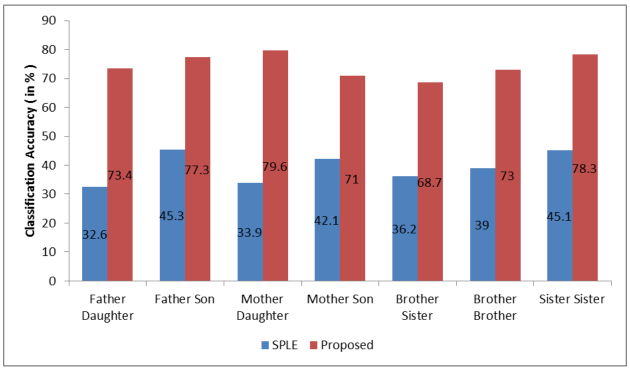

Figure 9. Classification results of the proposed SSRW and existing SPLE algorithms for different kinship relations on the IIITD kinship database.

	SPLE	Proposed SSRW
Child vs Young Parent	51.0%	55.3 %
Child vs Old Parent	48.4%	52.5%

Table 2. Average classification accuracy of SSRW and SPLE algorithms on the UB kinship database.

Figure 10. Analysis of the results: (a) correctly classified by both the algorithms, (b) incorrectly classified by both the algorithms, (c) correctly classified by SSRW but not classified by existing algorithm, and (d) correctly classified by existing algorithm but not by SSRW.

4. Conclusions and Future Research

This research proposes a novel self similarity representation of Weber faces for kinship classification. The proposed algorithm classifies the face images into kinship classes with a mean accuracy of 75.2% on the IIITD kinship database and up to 55.3% on the UB kinship database. The proposed algorithm also outperforms existing SPLE algorithm on both the databases. We plan to extend this research in two directions: (1) using registered face images as input to kinship classification and (2) extract and utilize contextual relationship for improving the performance.

5. Acknowledgement

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