



Article Title: Kinship Measurement on Face Images by Structured Similarity Fusion

Kinship Measurement on Face Images by Structured Similarity Fusion

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ABSTRACT

Kinship verification, which is a challenging problem in computer vision and pattern discovery. It has several applications, such as organizing photo albums, recognizing resemblances among humans, and finding missing children. A system for facial kinship verification based on several kinds of texture descriptors (local binary patterns, local ternary patterns, local directional patterns, local phase quantization, and binarized statistical image features) with pyramid multilevel (PML) face representation for feature extraction along with our proposed paired feature representation and our proposed robust feature selection to reduce the number of features. The proposed approach consists of the following three main stages: (1) face pre-processing, (2) feature extraction and selection, and (3) kinship verification. Extensive experiments are conducted on five publicly available databases (Cornell, UB KinFace, Family 101, KinFace W-I, and KinFace W-II). Additionally, a wide experiment for each stage to find the best and most suitable settings. Many comparisons with state-of-the-art methods and through these comparisons, it appears that our experiments show stable and good results.

Keywords: Kinship, Face analysis, Convolutional Neural Network, Pre-processing, Feature Extraction, Grayscale Images, Local Ternary Pattern.

1 Introduction

Automatic face analysis based on images has always been an important subject of study in the communities of pattern recognition and artificial intelligence. Facial images contain much information about the person they belong to, such as identity, age, gender, ethnicity, and expression. For this reason, the analysis of facial images has many applications in real-world problems such as face recognition, demographic estimation, facial expression recognition, and kinship verification. The recognition of kinship among people has mainly concentrated on studying the similarity between human faces. Indeed, there are four main types of kinship relationships: father–daughter (F–D), mother–son (M–S), father–son (F–S), and mother – daughter (M–D) relationships. Recently, other kinship relationship types have emerged, such as the relationship between grandparents and grandchildren. The recognition of kinship is a very challenging topic since the face conveys different facial features.

Currently, the recognition of the relationships between blood relatives has become an active area of research, and it has many applications, such as organizing a photo album, annotating images, and identifying lost or wanted people. Furthermore, the determination of kinship is no



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longer limited exclusively to genetic analysis; it cannot be used in many situations, but it is now extending to the field of biometrics and remote surveillance. The kinship verification problem has many difficulties, such as variations in age, gender, ethnicity, resemblances between persons without a real relationship, and differences in facial attributes between persons from the same family.

The proposed system is automatic facial kinship verification system that composed of three parts:

- 1) Face Pre-Processing
- 2) Feature Extraction
- 3) Kinship Verification.

In the face pre-processing stage, localize faces in images, rectifying the two-dimensional (2-D) pose of each face and crop the region of interest. Then extract the features by a texture descriptor using a pyramid multilevel (PML) face representation to obtain two feature vectors. These two feature vectors are transformed by the used features representation equation into a single features vector. These are then selected using our proposed feature selection method to obtain the best features and omit the bad features. The best features are fed to the Convolutional Neural Network (CNN) classifier to determine whether there is a kinship.

The evaluation of the performance of different texture descriptors: local binary patterns (LBP), local ternary pattern (LTP), local directional pattern (LDP), local phase quantization (LPQ), and binarized statistical image features (BSIF), along with the influences of other steps in the feature extraction stage. Investigated the efficiency of three different face image representations when combined with the above texture descriptors. The number of extracted features can be increased by varying the geometric layout of the face image representation in multiblock (MB), multilevel (ML), and PML. Our method shows the effectiveness of PML-based descriptors as a face descriptor in the feature extraction stage and the superiority of the PML-based LPQ descriptor. Investigated the best pair fusion scheme allowing fusion of the image paired features. Introduce an innovative robust feature score for feature ranking. This feature score is based on the use of the difference between two known weights. The new score can further improve the result of the kinship verification system. Many experiments are performed on five public databases (Cornell, UB KinFace, Family 101, KinFace W-I, and KinFace W-II) with good and stable results of the proposed approach compared with most of the state-of-the-art approaches.

2 Related Works

2.1 Towards Computational Models of Kinship Verification, Ruogu Fang

We tackle the challenge of kinship verification using novel feature extraction and selection methods, automatically classifying pairs of face images as “related” or “unrelated” (in terms of kinship). First, we conducted a controlled online search to collect frontal face images of 150 pairs of public figures and celebrities, along with images of their parents or children. Next, we



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propose and evaluate a set of low-level image features for this classification problem. After selecting the most discriminative inherited facial features, we demonstrate a classification accuracy of 70.67% on a test set of image pairs using K-Nearest-Neighbors. Finally, we present an evaluation of human performance on this problem.

Previous work in the field of face verification has typically used images of same people but in different lighting conditions, facial expressions, and environmental conditions. These different factors form challenges in the face verification problem, and have become the major focus of computer vision researchers in recent years. [1] Yet to the best of our knowledge, the work presented in this paper represents the first effort to automatically verify parent-child relationships in image pairs through the analysis of facial features. For this purpose, we first carry out a controlled ground truth data collection through on-line image searching based on knowledge of public figures and family photos.

In order to collect our training and testing data set, we collected 150 pairs of parents and children images from the Internet (Fig 1). Most of the images were found on Google Images, using text queries such as ‘George W. Bush’ and ‘George H.W. Bush’. To ensure that the facial features extracted are of high quality, the face images are selected to be frontal and a neutral facial expression. The database includes around 50% Caucasians, 40% Asians, 7% African Americans, and 3% others; 40% of the 150 images are father-son pairs, 22% are father-daughter, 13% are mother son, and 26% are mother-daughter. Therefore, it has a wide spread distribution of facial characteristics which depend on race, gender, age, career, etc.

2.2 Genealogical Face Recognition based on UB KinFace Database, Ming Shao

In this paper, we consider a challenging problem raised in biometric recently, genealogical face recognition. Practically, kinship can be proved via several methods, i.e., gene match. We argue in this paper that merely based on facial appearance can we present an accepted result on kinship verification, though there is remarkable appearance variance between kinship members. Essentially, as an extension of our former study, we proceed with the following work. First, an extended kinship database named “UB KinFace Ver2.0” is introduced. Second, we propose to use robust local Gabor filters to extract genetic-invariant features. Finally, metric learning and transfer subspace learning are adopted to abridge the great discrepancy between children and their old parents. The key idea is to take advantage of some intermediate data, e.g. young parents, close to both source and target data. Experimental results demonstrate the effectiveness of our kinship verification methods. Face recognition [25, 12, 19] attracts much attention over years. Several successful approaches [20, 4, 3, 2] have been proposed during past decades and meanwhile some benchmark databases, i.e., Yale B [10], CMU PIE [18] and FERET [15] have been publicly available for basic research. However, for the purpose of practical use, few of them are qualified materials applicable in the real world since these databases are constructed under well-controlled conditions. Essentially differed from them, an unconstrained database [11] called “Labeled Faces in the Wild” collects substantial typical face



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images in the real world which includes natural variations in factors. To attack this problem, two types of strategies are taken into consideration, 1) robust local features as well as specifically designed classifiers [13], and 2) heuristic information [5, 9, 8]. As to the second category, not only relevant text around image but also relation of human are utilized, e.g., kinship. Figure 1 shows some examples of kinship faces from UB KinFace database.

People with kin often appear in the same image, e.g., family album, and if used properly, it is able to assist identification for image database management, e.g., building family trees [22]. The baseline study of kinship verification within real-world domain was published in [8]. In that paper, key parts of faces are first localized to represent local information of faces, by which facial features such as skin color, gray value, histogram of gradient as well as facial structure information are extracted. Then K-Nearest Neighbor (KNN) with Euclidean metric is used for classification. Recently, we constructed a kinship database named “UB KinFace Ver1.0” [22] and proposed a transfer learning method to preliminarily solve the kinship verification problem across aging effect. The learning method is inspired by the commonly accepted genetics observation that faces of parents captured while they were young are more alike their children’s compared with images captured when they were old. Therefore, transfer learning can act as a bridge to essentially reduce the divergence of aging effect between the elder and young faces.

2.3 Self-Similarity Representation of Weber Faces for Kinship Classification, Naman Kohli, Richa Singh, Mayank Vatsa

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 preprocessed 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%.

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



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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.

2.4 Neighborhood Repulsed Metric Learning for Kinship Verification, Jiwen Lu

Kinship verification from facial images is a challenging problem in computer vision, and there is a very few attempts on tackling this problem in the literature. In this paper, we propose a new neighborhood repulsed metric learning (NRML) method for kinship verification. Motivated by the fact that interclass samples (without kinship relations) with higher similarity usually lie in a neighborhood and are more easily misclassified than those with lower similarity, we aim to learn a distance metric under which the intraclass samples (with kinship relations) are pushed as close as possible and interclass samples lying in a neighborhood are repulsed and pulled as far as possible, simultaneously, such that more discriminative information can be exploited for verification. Moreover, we propose a multiview NRML (MNRML) method to seek a common distance metric to make better use of multiple feature descriptors to further improve the verification performance. Experimental results are presented to demonstrate the efficacy of the proposed methods.

2.5 Discriminative Multimetric Learning for Kinship Verification, Haibin Yan

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.

3 Proposed Work

Proposed a discriminative multimetric learning (DMML) method for kinship verification. First, they extracted multiple features using different face descriptors; then, they jointly learned multiple distance metrics for those descriptor features under which the probability of a pair of face images where the kinship relation had a smaller distance than the pair that had no kinship relation.

In their work, they applied their method to two databases: Cornell and UB KinFace databases. Proposed another approach based on the selected deep features of the VGGFACE descriptor using the Fisher score. They applied their approach on five databases (Cornell, UB KinFace, Family 101, Kinface W-I, and KinFace W-II). Wang et al.19 proposed a young cross-



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generation model for kinship verification. They used a deep architecture with a newly designed sparse discriminative metric loss for features extraction and applied their method on the (families in the wild) databases.

The evaluation of the performance of different texture descriptors: local binary patterns (LBP), local ternary pattern (LTP), local directional pattern (LDP), local phase quantization (LPQ), and binarized statistical image features (BSIF), along with the influences of other steps in the feature extraction stage. The efficiency of three different face image representations when combined with the above texture descriptors.

The number of extracted features can be increased by varying the geometric layout of the face image representation in multiblock (MB), multilevel (ML), and PML. Our method shows the effectiveness of PML-based descriptors as a face descriptor in the feature extraction stage and the superiority of the PML-based LPQ descriptor.

Investigated the best pair fusion scheme allowing fusion of the image paired features. An innovative robust feature score for feature ranking. This feature score is based on the use of the difference between two known weights. The new score can further improve the result of the kinship verification system.

3.1 Kinship Verification Approach Architecture for the Proposal Platform

The proposed approach of kinship verification is the operation of using two people's faces to determine whether there is a familial relationship between them. Our proposed method consists of three stages: (1) face preprocessing: for detecting and cropping human faces from an input image; (2) feature extraction: using different descriptors (LBP, LDP, LTP, LPQ, and BSIF), and face representation: with different methods (MB, ML, and PML), (3) classification stage: feature representation and normalization, feature selection (Fisher score, t-test, Kullback-Leibler (KL), and the proposed feature selection), and the decision of the kinship verification with an SVM classifier. Figure 1 illustrates the general structure of the proposed framework.

3.1.1 Face Pre-processing

Face pre-processing is a very important stage and it consists of three steps:

- (I) Face Detection
 - (II) Eye Detection
 - (III) Face Cropping
- (I) Apply the cascade object detector, which uses the Viola-Jones algorithm²⁰ to detect people's faces.
 - (II) It detect the right and left eye positions using the ensemble of regression trees algorithm.²¹ For pose correction, it apply 2-D transformation based on the eye center to correct the pose.²²
 - (III) To crop the face region of interest, rescale the face image via normalizing the distance between the new coordinates of the two eyes and then crop the image based



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on these coordinates.23. Finally, the cropped facial images are resized to 224×224 . Figure 2 presents the steps in this stage.

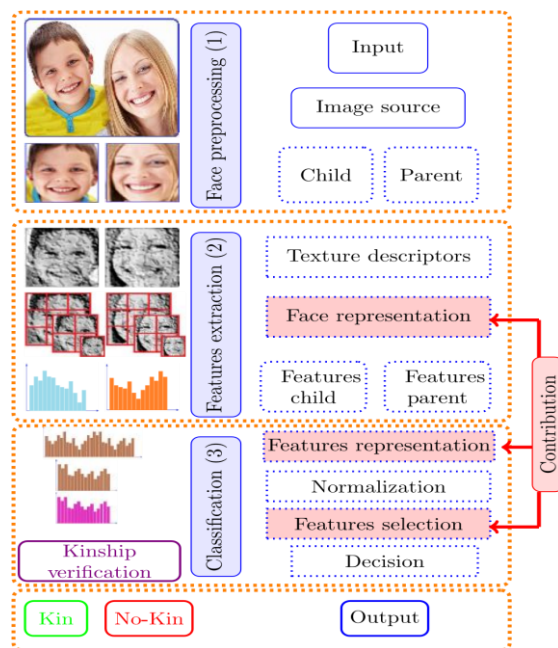


Figure 1: General structure of the proposed approach

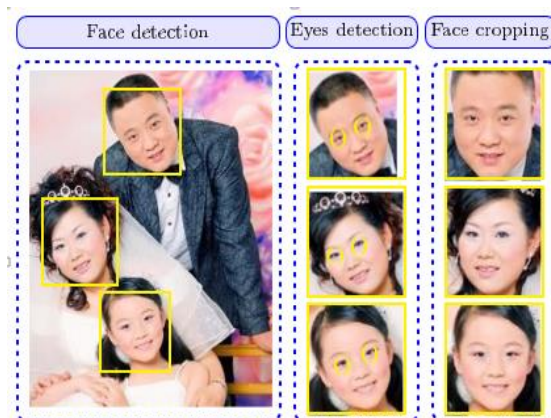


Figure 2: Face pre-processing steps

3.1.2 Feature Extraction

The feature extraction stage has been the most studied topic among the remaining stages due to its effectiveness on facial kinship verification system performance. It divided our feature extraction stage into two parts. In the first part, it present the different texture descriptors used in our work. In the second part, the different face representations are illustrated.



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3.1.3 Image Texture Descriptor

In the image classification field, there are many image texture descriptors that can be used in facial kinship verification or that have already been used in this field. In our work, it use five widely known image texture descriptors: LBP, LTP, LDP, LPQ, and BSIF.

LBP. The LBP was proposed by Ojala et al.²⁴ The LBP is one of the most well-known descriptors, which has led to the development of many descriptors. The LBP is a local descriptor that extracts the local features from image I by thresholding the value of each pixel with its neighborhood pixels using the function S_{LBP} , which is defined as where z is the the result of subtracting the center pixel value from the intended neighborhood pixel value. The LBP is denoted by $\text{LBPP}; R$, where P is the number of neighborhoods that are equally spaced on a circle of radius R from the center pixel. Each thresholding process between the center pixel value and a neighbourhood produces a binary value. The number of bins is 2^P , so the bin value is between 0 and 2^P-1 . After the thresholding of the pixel and its neighborhoods, a histogram is used to accumulate the occurrence of the various bins over a region.

3.1.4 Face Representation

MB. The most common face representation in image processing is a regular grid of fixed size regions that it call MB representation. MB face representation divides the image into n^2 blocks where n is the intended level of MB. Figure 8 illustrates the MB face representations.

ML. Recently, a similar representation called ML was used in the age estimation and gender classification topics.³⁰ ML face representation is a spatial pyramid representation constructed by a sorted series of MB representations. The ML face representation level n is constructed from level 1;:::; n MB representations. Figure 9 illustrates the ML face representations.

PML. PML face representation is an approach that extracts the local texture features using different descriptors and adopts an explicit pyramid representation of the original image. This pyramid represents the image at different scales. For each such level or scale, a corresponding MB representation is used. PML sub-blocks have the same size, which is determined by the image size and the chosen level. The main idea of the PML is to extract features.

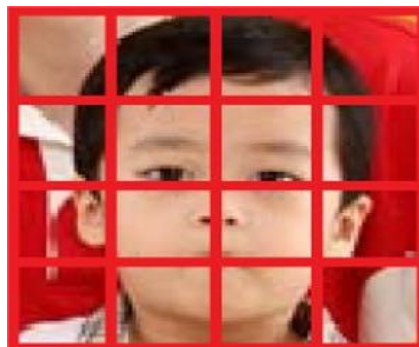


Figure 3: Multiblock example of four levels.



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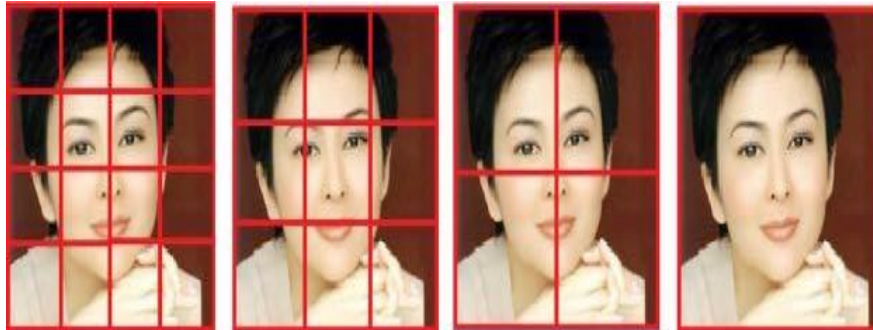


Figure 4: A multilevel representation adopting four levels

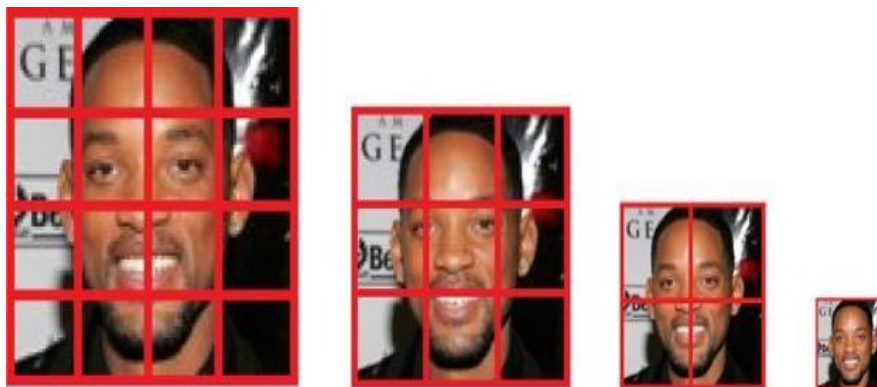


Figure 5: PML example of four levels

3.1.5 Classification

The last stage in our proposed approach is the classification stage where the decision for kinship verification is made. It is composed of, the two feature vectors (child/parent) are fused into one feature vector. After having the paired features representation vector, it normalized the final feature vector. Due to the large number of features obtained from the different face representations, it propose to reduce the number of features using different feature selections along with our proposed approach.

The last step in the classification uses the SVMs to determine whether there is kinship or not. SVM constructs a hyperplane or set of hyperplanes in a high-dimensional space, which can be used for classification or regression tasks. Intuitively, good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (the so-called functional margin), since, in general, the larger the margin is, the lower the generalization error of the classifier.



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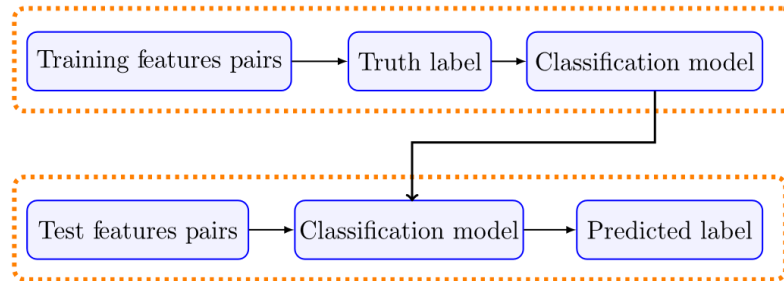


Figure 6: Evolution Process

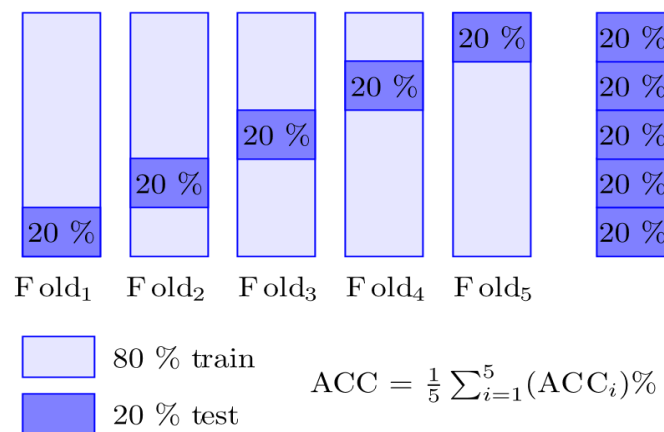


Figure 7: Fivefold Cross Validation

It used the binary SVM classifier to train and test our proposed approach. The two binary classes are either a kinship relationship or not, which are represented by 1 and 0, respectively. The evaluation process has two steps. The first step consists of training the SVM models using the training pairs. The second step predicts the class of all pairs in the test set.

It adopt a fivefold cross-validation scheme for evaluation. In this scheme, 80% of the data are used for training and the remaining data are used for testing. Figure 12 illustrates the two steps of the evaluation process.

K-fold cross validation is a standard protocol that allows the evaluation of a given algorithm or a classifier.

It proceeds as follows. First, the whole dataset is split into k subsets. One subset is chosen as a test set and the remaining k – 1 subsets are used for training. This process is repeated k times to ensure that all data are used in the test. The final performance is set to the average performance over the k folds.

Illustrates the principle of k-fold cross validation when k is equal to five. The classification algorithm is trained five times on as many different data segments and five independent tests are conducted thereafter. The number of subsets can be modified to meet the particular needs of an experiment.



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3.1.6 Cornell Kinface (2010)

The Cornell KinFace database is the first database that was used for kinship verification. It was created by

Fang et al. from the University of Cornell. They collected 150 pairs (300 images). With variations in demographic attributes. The distribution of the kinship pairs is follows: 40% (F–S), 22% (F–D), 13% (M–S), and 26% (M–D).

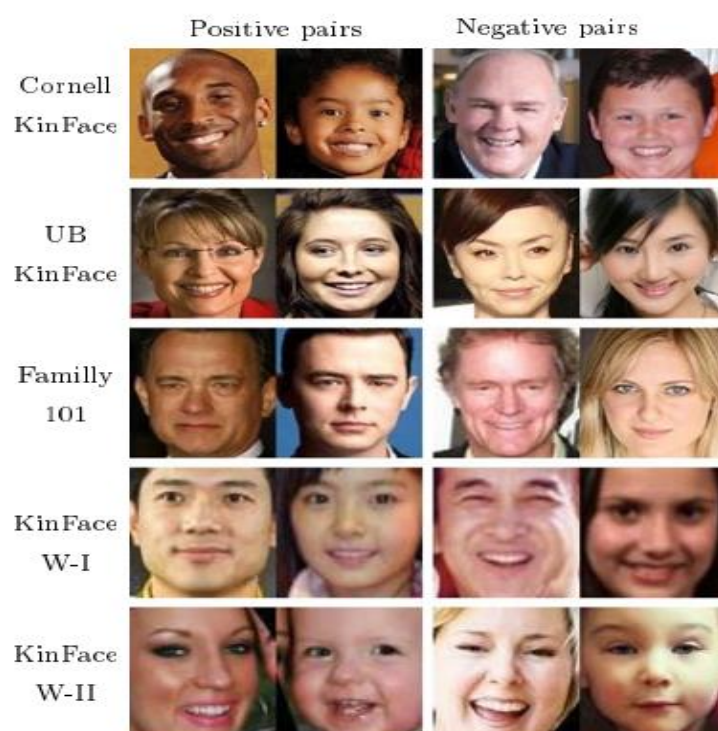


Figure 8: Examples of positive and negative pairs from used databases

3.2 Modules

Load Image: In the context of kinship verification, "load image" refers to the process of reading and acquiring the image data from a file or any other source in order to perform analysis and verification tasks related to familial relationships. The image is typically a facial image of an individual or a pair of individuals that will be used for kinship verification.

Input Source: The image to be loaded can come from various sources such as a local file system, a remote server, a database, or even real-time video streams. The specific source depends on the application and the availability of the image data.

Image Format: Images can be in different formats such as JPEG, PNG, BMP, or TIFF. The "load image" process should handle different image formats and ensure compatibility with subsequent processing steps.



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Image Pre-processing: Pre-processing images is an important step in kinship verification as it helps improve the quality of the images and enhances the effectiveness of subsequent analysis and feature extraction methods. Here are some common pre-processing techniques used in kinship verification.

Image Resizing: Resizing the images to a standard size is often necessary to ensure consistency in the analysis. It helps align the faces and reduces variations due to image dimensions. Resizing also helps in reducing computational complexity during subsequent processing steps.

Face Detection and Alignment: Accurate face detection is crucial for kinship verification. Face detection algorithms are used to locate and extract facial regions from the images. Once the faces are detected, face alignment techniques can be applied to normalize the poses and orientations, making the subsequent analysis more robust. Techniques such as facial landmark detection or geometric transformations can be used for face alignment.

Image Enhancement: Image enhancement techniques can be employed to improve the visual quality of the images. These techniques aim to enhance the contrast, brightness, and sharpness of the images. Histogram equalization, adaptive contrast enhancement, or filtering techniques like Gaussian or unsharp masking can be used for image enhancement.

Noise Removal: Images may contain various types of noise, such as Gaussian noise or salt-and-pepper noise, which can adversely affect the analysis. Applying denoising techniques such as median filtering, bilateral filtering, or wavelet denoising can help remove noise while preserving important facial details.

Illumination Normalization: Illumination variations can introduce challenges in kinship verification. Illumination normalization techniques can be used to reduce the impact of lighting variations and make the images more consistent.

Grayscale Conversion: Converting color images to grayscale is often preferred in kinship verification to simplify the analysis and reduce computational complexity. Grayscale conversion helps focus on the facial structures and textures, disregarding color information. This conversion can be done by taking the weighted average of the color channels or using specific color-to-grayscale conversion formulas.

Gray scale and face representation: Grayscale and face representation play important roles in kinship verification, especially when analysing facial features for determining familial relationships. Here's how grayscale and face representation are relevant in the context of kinship verification.

Grayscale Images: Grayscale images are single-channel images that represent the intensity of each pixel without color information. They are commonly used in kinship verification because they simplify the analysis and reduce computational complexity. Grayscale images contain valuable information about facial structures, textures, and patterns, which can be leveraged for kinship verification tasks.

Facial Feature Extraction: In kinship verification, facial features are extracted from grayscale images to capture the relevant characteristics for identifying familial relationships. Techniques



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such as facial landmarks detection, facial expression analysis, or deep learning-based methods can be employed to extract facial features. These features may include the shape of the eyes, nose, mouth, and the arrangement of facial landmarks.

Face Representation: Once facial features are extracted, they need to be represented in a suitable format for kinship verification. Different approaches can be used to represent facial features, including holistic representations and local feature descriptors.

Holistic Representations: Holistic representations capture the entire face as a whole and encode the extracted features into a fixed-length vector.

Multilevel processing: Multilevel processing is a concept that can be applied to kinship verification, which is the task of determining the familial relationship between two individuals based on their facial or genetic features. By employing multilevel processing techniques, an analyze kinship verification from different perspectives and at multiple stages, enhancing the accuracy and robustness of the verification process. Here's a brief overview of how multilevel processing can be applied to kinship verification.

Feature Extraction: The first level of processing involves extracting relevant features from facial or genetic data. For facial kinship verification, facial landmarks or deep learning techniques can be used to extract discriminative facial features such as the shape of the eyes, nose, and mouth. In genetic kinship verification, genetic markers or sequences are analysed to identify relevant patterns.

Representation Learning: In the second level, extracted features are further processed to obtain more meaningful representations. This step aims to reduce noise, enhance discriminative information, and capture high-level characteristics of kinship traits. Techniques such as dimensionality reduction, feature fusion, or deep learning architectures like convolutional neural networks (CNNs) can be employed for representation learning.

Similarity Measurement: At this level, the representations obtained from the previous step are compared to measure the similarity or dissimilarity between two individuals. Various distance metrics or similarity measures can be used depending on the nature of the data. For example, cosine similarity, Euclidean distance, or correlation coefficients can be utilized for facial kinship verification.

Decision Fusion: In multilevel processing, decisions from different stages are combined to obtain a final kinship verification result. The decisions can be fused using techniques such as majority voting, weighted averaging, or ensemble methods. This step helps in incorporating multiple levels of information to improve the overall accuracy and reliability of the verification process.

Feature Extraction: This module will extract multiscale and multilevel handcrafted features from the preprocessed facial images. The module will use techniques such as Local Binary Patterns (LBP), Scale Invariant Feature Transform (SIFT), and Principal Component Analysis (PCA) to extract meaningful features. These features will then be used as input for the classification models.



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Performance Evaluation: This module will evaluate the performance of the kinship verification system. The module will use metrics such as accuracy, precision, recall, and F1 score to assess the effectiveness of the system. The module will also include techniques such as ROC curve analysis, and confusion matrix analysis to evaluate the performance of the models.

Kinship Verification: This module will use the extracted features to verify kinship between pairs of individuals. The module will use machine learning algorithms, such as convolutional neural networks (CNN), to classify the pairs of individuals as either kin or non-kin. The module will utilize different techniques such as cross-validation and hyper-parameter tuning to improve the performance of the models.

4 Result and Discussion

After developing a kinship verification system using facial images, the model's performance needs to be evaluated and discussed. Here are some aspects to consider when analyzing the results:

Evaluation Metrics: Assess the performance of the kinship verification system using appropriate evaluation metrics. Commonly used metrics include accuracy, precision, recall, F1 score, and receiver operating characteristic (ROC) curve analysis.

Dataset and Data Imbalance: Discuss the characteristics of the dataset used for training and testing the model. Ensure the dataset represents a diverse range of kinship relationships and includes a balanced representation of kin and non-kin pairs. Address any potential data imbalance issues and their impact on the model's performance.

Performance on Kin and Non-Kin Pairs: Analyze the accuracy and performance of the system in identifying both kin and non-kin pairs. Determine if the system is equally effective in correctly classifying both types of relationships or if there is a bias towards one category.

Impact of Image Variations: Discuss the system's robustness against variations in facial images, such as pose, lighting conditions, occlusions, and image quality. Evaluate if the system's performance remains consistent across different image variations or if certain variations pose challenges for accurate kinship verification.

Comparison with Baseline Models: Compare the developed kinship verification system with existing baseline models or state-of-the-art methods. Evaluate if the proposed system outperforms or is on par with existing approaches in terms of accuracy and robustness.

Limitations and Challenges: Discuss the limitations and challenges encountered during the development of the kinship verification system. Address any specific cases or scenarios where the system may struggle to accurately determine kinship relationships. Identify areas for improvement and potential directions for future research.

Real-World Applicability: Assess the practical applicability of the developed system in real-world scenarios. Discuss its potential use in fields such as genealogy, forensic science, or social network analysis. Consider any ethical considerations or limitations when deploying the system in practice.



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Future Work: Identify opportunities for future research and improvements. Discuss potential enhancements to the system, such as incorporating additional modalities (e.g., DNA analysis, voice recognition) for more robust kinship verification or exploring new deep learning architectures for improved accuracy.

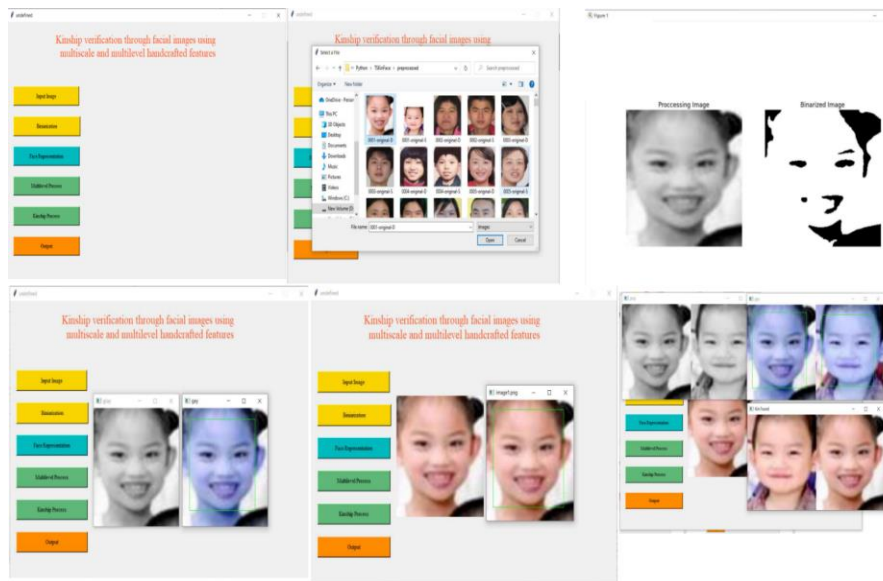


Figure 9: Kinship Process

5 Conclusion

Facial kinship verification based on different descriptors with PML face representation. A new paired feature representation and a new feature weighting is introduced. Different kinds of effects investigated, including image texture descriptors and face and feature representations. The experimental results showed that our approach provides good performance and stable results on five publicly available databases compared to the previous approaches. In future work, the propose using deep features provided by models such as VGGNet, AlexNet, ResNet, and ImageNet. Moreover, envision developing CNN architectures for multitask estimation. Additionally, envision the use of other soft biometric traits, such as age and gender, to improve the kinship verification accuracy.

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