FUSION FEATURES ENSEMBLING MODELS USING SIAMESE CONVOLUTIONAL NEURAL NETWORK FOR KINSHIP VERIFICATION

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DEDICATION

To Allah (﷾), the Entirely Merciful, the Especially Merciful

To Prophet Muhammad (ﷺ) and His Companions (رضي الله عنهم)

To my beloved Father (ALI) "may Allah have mercy on him" and Mother (ZAHRA)
To my brothers and sisters

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ABSTRACT

Family is one of the most important entities in the community. Mining the genetic information through facial images is increasingly being utilized in wide range of real-world applications to facilitate family members tracing and kinship analysis to become remarkably easy, inexpensive, and fast as compared to the procedure of profiling Deoxyribonucleic acid (DNA). However, the opportunities of building reliable models for kinship recognition are still suffering from the insufficient determination of the familial features, unstable reference cues of kinship, and the genetic influence factors of family features. This research proposes enhanced methods for extracting and selecting the effective familial features that could provide evidences of kinship leading to improve the kinship verification accuracy through visual facial images. First, the Convolutional Neural Network based on Optimized Local Raw Pixels Similarity Representation (OLRPSR) method is developed to improve the accuracy performance by generating a new matrix representation in order to remove irrelevant information. Second, the Siamese Convolutional Neural Network and Fusion of the Best Overlapping Blocks (SCNN-FBOB) is proposed to track and identify the most informative kinship clues features in order to achieve higher accuracy. Third, the Siamese Convolutional Neural Network and Ensembling Models Based on Selecting Best Combination (SCNN-EMSBC) is introduced to overcome the weak performance of the individual image and classifier. To evaluate the performance of the proposed methods, series of experiments are conducted using two popular benchmarking kinship databases; the KinFaceW-I and KinFaceW-II which then are benchmarked against the state-of-art algorithms found in the literature. It is indicated that SCNN-EMSBC method achieves promising results with the average accuracy of 92.42% and 94.80% on KinFaceW-I and KinFaceW-II, respectively. These results significantly improve the kinship verification performance and has outperformed the state-of-art algorithms for visual image-based kinship verification.

ABSTRAK

Keluarga adalah merupakan salah satu entiti yang terpenting dalam sesuatu komuniti. Perlombongan makumat genetik melalui kaedah pengimejan muka telah semakin meluas digunakan dalam pelbagai aplikasi dunia nyata bagi membantu menjejaki ahli keluarga dan analisis kekeluargaan menjadi mudah, murah dan cepat berbanding dengan prosedur pemprofilan Deoxyribonucleic acid (DNA). Walau bagaimanapun, peluang untuk membangunkan model yang boleh dipercayai untuk pengecaman kekeluargaan masih lagi mempunyai kekurangan dari aspek penentuan ciri-ciri kekeluargaan, ketidakstabilan penunjuk rujukan kekeluargaan, dan juga faktor-faktor pengaruh genetik sifat keluarga. Kajian ini mencadangkan penambahbaikan kaedah untuk mengekstrak dan memilih ciri-ciri kekeluargaan yang efektif yang boleh memberikan bukti kekeluargaan dan menjurus kepada peningkatan ketepatan terhadap pengenalpastian kekeluargaan di dalam pengesahan dan pengelasan melalui pengimejan visual muka. Pertamanya, kaedah Neural Network based on Optimized Local Raw Pixels Similarity Representation (OLRPSR) telah dibangunkan untuk memperbaiki ketepatan prestasi melalui penjanaan perwakilan matriks baru untuk menyisihkan maklumat yang tidak berkenaan. Keduanya, Siamese Convolutional Neural Network and Fusion of the Best Overlapping Blocks (SCNN-FBOB) telah dicadangkan untuk menjejak dan mengenal pasti petunjuk kekeluargaan yang paling bermaklumat demi mencapai ketepatan yang tinggi. Ketiganya, Siamese Convolutional Neural Network and Ensembling Models Based on Selecting Best Combination (SCNN-EMSBC) telah juga diperkenalkan untuk mengatasi prestasi lemah untuk imej individu serta pengelas. Untuk menilai prestasi semua kaedah yang telah dicadangkan, beberapa siri eksperimen telah dikendalikan dengan menggunakan dua pangkalan data penanda aras kekeluargaan yang popular: KinFaceW-I, KinFaceW-II, yang seterusnya ditanda aras dengan menggunakan algoritma yang terdapat di literatur. Ianya menunjukkan bahawa kaedah verifikasi SCNN-EMSBC telah mencapai keputusan yang memberangsangkan dengan mencapai ketepatan purata terhadap KinFaceW-I (92.42%) dan KinFaceW-II (94.80%). Dapatan-dapatan ini telah memperbaiki secara signifikan prestasi pengecaman kekeluargaan dan telah mengatasi algoritma terkini untuk pengecaman kekeluargaan berdasarkan imej visual muka.

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AI	-	Artificial Intelligence
ANN	-	Artificial Neural Networks
ACC	-	Accuracy
API	-	Application Program Interface
ANN	-	Artificial Neural Network
BP	-	Back-Propagation
BSIF	-	Binarized Statistical Image Features
CFT	-	Coarse-To-Fine Transfer
CG	-	Combinations Generator
CNN	-	Convolutional Neural Network
CS	-	Cosine Similarity
DA	-	Data Augmentation
dB	-	Decibel
DBN	-	Deep Belief Network
DL	-	Deep Learning
DNA	-	Deoxyribonucleic Acid
DFT	-	Discrete Fourier Transform
DDML	-	Discriminative Deep Metric Learning
DMML	-	Discriminative Multi-Metric Learning
FE	-	Feature Extraction
FL	-	Feature Learning
fcDBN	-	Filtered Contractive Deep Belief Networks
FPLBP	-	Four-Patch Local Binary Pattern
DoG	-	Gaussian Function
GAN	-	Generative Adversarial Network
GG	-	Genetic Genealogy
GPU	-	Graphics Processing Unit
HOG	-	Histogram of Oriented Gradients
HSV	-	Hue, Saturation, Value
Tanh	-	Hyperbolic Tangent

ICA	-	Independent Component Analysis
KNN	-	K-Nearest Neighbour
LM^3L	-	Large-Margin Multi-Metric Learning
lr	-	Learning Rate
LDA	-	Linear Discriminant Analysis
LBP	-	Local Binary Pattern
LPQ	-	Local Phase Quantization
LSTM	-	Long Short-Term Memory
ML	-	Machine Learning
MSE	-	Mean Square Error
MNRML	-	Multiview Neighbourhood Repulsed Metric Learning
NRML	-	Neighbourhood Repulsed Metric Learning
NFL	-	No Free Lunch
PLBP	-	Patch Based Local Binary Pattern
PSNR	-	Peak Signal-To-Noise Ratio
PCA	-	Principal Component Analysis
RBF	-	Radial Basis Function
ReLU	-	Rectified Linear Unit
RNN	-	Recurrent Neural Network
RGB	-	Red, Green, Blue
ResNet	-	Residual Neural Network
S^3L	-	Structured Sparse Similarity Learning
SIFT	-	Scale Invariant Feature Transform
STFT	-	Short-Term Fourier Transform
SCNN	-	Siamese Convolutional Neural Network
SMCNN	-	Similarity Metric Based Convolutional Neural Network
SGD	-	Stochastic Gradient Descent
SSIM	-	Structural Similarity Measurements
SVM	-	Support Vector Machine
VGG	-	Visual Geometry Group
WLD	-	Weber Local Descriptor
WGEML	-	Weighted Graph Embedding Based Metric Learning

CHAPTER 1

INTRODUCTION

1.1 Introduction

Biometric is physiological and behavioural traits measurements originate from the human which used by human and machine to recognize individuals (Council and Committee, 2010). In fact, a face is a physiological characteristic that holds much and diverse types of information and exciting details, where the humans can use this information to reveals the human characteristics of kinship, gender, age, race, and others. However, humans in some cases can easily recognizing people in images by their faces (Hettiachchi *et al.*, 2020). This skill is quite robust against significant changes in facial features such as illumination, noise, aging, and hairstyle (Sinha *et al.*, 2006).

The booming of big data in recent years witnesses digital photo being shared across many media platforms. Potential relationship in photos include those among kin, colleagues, and friends. Analysing facial images is one of the major research topics in computer vision and pattern analysis. In the past few decades, face recognition problems have been the focus of considerable attention and algorithms have also been shown to perform effectively under the controlled and uncontrolled environments using different databases (Fredj *et al.*, 2020). Recently, due to genetic transmission (e.g., from parent to offspring), there is most likely to be facial characteristics similarities between family members. Thus, the researchers deliberately to analyse, understand and processing face images in order to identify kin relationship.

Family resemblance, which is caused by the transmission of genetic traits through generations, relates to physical similarities commonly associated between close relatives, particularly between parents and their offspring and between siblings. The kinship refers to the genetic relatedness, similarities and blood ties between individual members of the same family (Wang *et al.*, 2020c). However, kinship recognition is becoming a new research area for image-based in computer vision and has significantly increased concern in recent years. In computer vision, kinship recognition is a mission of training a machine to classify and distinguish the blood ties between pairs based on visual information acquired from face image. In the other words, capability for discriminating kins from unrelated people based on the facial images. Figure 1.1 exhibits cases of the kinship verification problem, where given a pair of images, the target is to deciding whether two individuals are kin or not, or to determine relevant family based on resemblances in appearance.

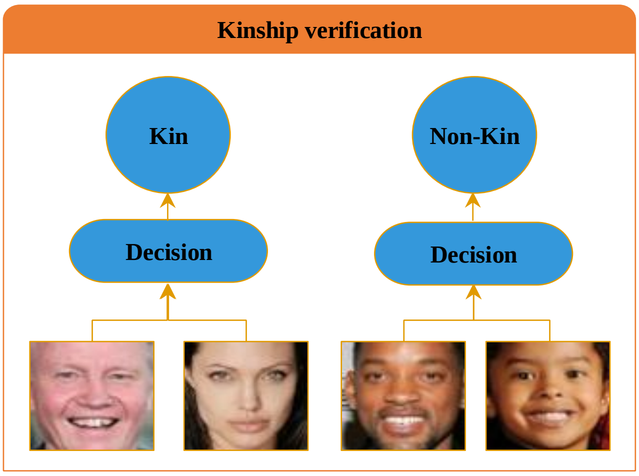

Figure 1.1 Example of the face-based kinship verification problem

Kinship has been extensively studied in various scientific fields like psychology and computer vision. In the domain of psychology, several scientists have investigated the ability of human observers of recognizing kinship through similarity cues captured from facial images (Dal Martello and Maloney, 2006; DeBruine *et al.*, 2009; Froelich and Nettleton, 2013; Kaminski *et al.*, 2009; Park *et al.*, 2008). However, kinship can often be judged by calculating and considering the resemblance among facial regions between individuals. Thus, the biological similarities between traits found in the same family and also the psychological findings inspire researchers to take advantage of these facts to design and develop a computer-based system that can be able to recognize kinship automatically. In the field of computer vision and machine learning, kinship recognition research started in 2010 by Fang *et al.* (2010). The computer-aided kinship recognition is a method that helps in studying and analysing the phenotypic properties that are reflected on the appearance of the face.

Computational systems function via generating discriminatory features and informative information using for kinship measurement. Hence, it is important to determine the structural kin-relationship meaning for understanding the nature of familial traits and discovering an accurate model (Duan *et al.*, 2017a). However, the computer vision and machine learning communities have devoted a lot of effort towards determining and tracking features responsible for providing kinship signals helping to build new reliable models that can improve performance. However, despite the development of computerized models over the past few years, they are inaccurate while recognizing the kinship due to the inherent complexity of this problem (Qin *et al.*, 2020) that increase the misclassification error rate. Thus, the researchers must ensure define a set of stable features strictly associated with the familial traits during the model building stage, as the observation of adopting the deceptive clues that generates inaccurate features which can affect the efficiency of model.

To date, different methods related to the detecting the discriminatory familial traits for recognizing kinship have been proposed. However, the results obtained under the current frameworks are providing unsatisfactory accuracy performance and reliability. Accordingly, extracting prominent familial features increases the opportunity to develop intelligent models to help overcome challenges, and enhances the ability to determine effective and precise cues indicating kin relationship from the appearance of the face, hence improving the overall accuracy performance of the kinship system.

The focus of the research in this domain has been on automatically discovering familial traits from images in order to recognize kinship. In this research, the key issue of automatic kinship recognition system mainly focuses on the problem of kinship verification, as visually seen in Figure 1.1. The kinship verification refers to a system intended to determine if the given pair of facial images are kin or not. This task is one-to-one classification problem with model responses being either related or unrelated.

1.2 Problem Background

Understanding and analysing a family relationship based on face is a challenging for computer systems. As a result, many algorithms have been proposed in the literature for automatic face-based kinship recognition utilizing different machine learning techniques, which categorized into two groups; feature-based and learning-based (Kou *et al.*, 2015; Wei *et al.*, 2019; Xu and Shang, 2016a; Yan *et al.*, 2014b).

The feature-based methods generally extract discriminative feature from face image in order to characterize the genetic traits (genetic information) on between a parent and their children. This type of method is also divided into two groups: the first utilizing handcrafted features (Dibeklioglu *et al.*, 2013; Dong *et al.*, 2014; Fang *et al.*, 2010; Laiadi *et al.*; Van and Hoang, 2019b; Yan, 2019; Zhou *et al.*, 2011) and the second utilizing deep features learning (Dehghan *et al.*, 2014; Li *et al.*, 2016; Luo *et al.*, 2020; Robinson *et al.*, 2018; Wang *et al.*, 2015a; Yu *et al.*, 2020a; Yu *et al.*, 2020b). However, the majority existing methods of kinship recognition have adopted for handcrafted features (Qin *et al.*, 2020).

Existing feature extraction methods which have been used to learn feature representations from the facial images in regards to handcrafted features, i.e., local binary pattern (LBP) (Alirezazadeh *et al.*, 2016; Patel *et al.*, 2017; Yan *et al.*, 2014a), local phase quantization (LPQ) (Alirezazadeh *et al.*, 2016; Laiadi *et al.*; Zhao *et al.*, 2018), histogram of oriented gradients (HOG) (Dong *et al.*, 2014; Mahpod and Keller, 2018; Xu and Shang, 2016b), scale invariant feature transform (SIFT) (Dong *et al.*, 2014; Xu and Shang, 2016b; Yadav *et al.*, 2019), Gabor wavelet (Somanath and Kambhamettu, 2012; Xia *et al.*, 2012b; Zhou *et al.*, 2012), colour and facial distances (Fang *et al.*, 2010). Whilst deep belief network (Kohli *et al.*, 2016), autoencoder (Dehghan *et al.*, 2014; Kohli *et al.*, 2016; Wang *et al.*, 2015a), and convolutional neural network (Chergui *et al.*, 2019a; Chergui *et al.*, 2019c; Crispim *et al.*, 2020; Guo *et al.*, 2018; Rehman *et al.*, 2019) are for deep features learning.

The intrinsic characteristics of this very complex problem, for example facial appearance variance which makes a large distribution gap between parent and children, creates considerable challenges for the kinship algorithms. However, the results of feature-based methods are limited due to their less capability of simulating and modelling human ability and interactions in a difficult environment. In regards to handcrafted feature, which is also described as shallow feature that chosen to represent characteristics of the image, is incapable of describing the visual resemblance between biologically-related pair of face precisely (Li *et al.*, 2017; Xia *et al.*, 2018) because of its inflexibility, require domain knowledge expertise (Simonyan and Zisserman, 2014) general representation and lack of distinctiveness (Masi *et al.*, 2018).

On the other hand, in spite of the success of deep feature learning, existing solutions to modelling kinship recognition still suffer from some critical problems that hinder the effective use of such method. The insufficient database will affect functionality of deep learning algorithms (Najafabadi *et al.*, 2015), thus affect to obtain more expressive representation and the modelling of kinship recognition particularly (Li *et al.*, 2017). Therefore, the extremely extensive data is necessary to be collected containing extreme variation and balance in terms to number of families, members, images illumination, pose, and many others in order to meet challenges of kinship recognition. Moreover, these deep feature learning has limited capablity to fully and accurately define the underlying familial features among the kinship-related people.

Another possible problem may result when using the deep learning algorithms is that the models are characterized as a black box and lack of transparency and interpretability (Buhrmester *et al.*, 2019; Georgopoulos *et al.*, 2018; O'Mahony *et al.*, 2019), which makes comprehension of how features represent kinship recognition cues very hard (Qin *et al.*, 2020). However, as models learn through databases, they are likely to be subjected to unfair biases due to the contaminated data content (Buhrmester *et al.*, 2019). However, CNN-based features can use cues such as background, clothing, colours and shadows as an input data that taken from the same photograph, which can reduce some challenges (Yan *et al.*, 2014a). Nevertheless, it may make the model more challenging to recognize kinship (Li *et al.*, 2017), and can learn visual similarities rather than learning the valid familial traits characteristics implied in kin-relationship (Dawson *et al.*, 2018). Thus, may giving confusing inferential indications and consequently false classification results.

Typically, the convolution neural network (CNN), as for example, aims to automatically extract a discriminative features, however, most existing models treat all the images samples of parents and children equally without consideration of other factors such as age gaps, and distribution difference (Duan *et al.*, 2017a). Additionally, since different kin relationship between each image pair of the same family as well as among families render different similarity features, it is imperative to address each kin relation differently during the training of model (Lopez *et al.*, 2018).

Furthermore, the single deep learning model for kinship recognition remain yet to be suffered from the generalization ability. According to the *no free lunch (NFL)* theorem (Fernández-Delgado *et al.*, 2014; Wolpert, 1996; Wolpert and Macready, 1997), no single model is significantly superior on every dataset. Therefore, tries various methods to train, test and select the best models might increase the generalization ability and improve the performance.

In contrast, the learning-based methods such as metric learning (Kaya and Bilge, 2019), usually focus on statistical learning techniques, in which the training data will used to learn an appropriate distance metric that able to distinguish kinship by increased the distance between the non-kin relationship samples as possible and decreased the distance between the kin relationship samples as possible simultaneously.

However, many various methods (Fang *et al.*, 2016; Hu *et al.*, 2017a; Hu *et al.*, 2017b; Li *et al.*, 2016; Li *et al.*, 2017; Liang *et al.*, 2018; Liu and Zhu, 2017; Lu *et al.*, 2017; Lu *et al.*, 2013; Yan *et al.*, 2014a; Zhou *et al.*, 2019) have been proposed to solve different issues into kinship recognition. The above-mentioned feature types can be utilized as feature representations methods for facial images to build the feature subspace. In particular, handcrafted features are used in (Fang *et al.*, 2016; Hu *et al.*, 2017a; Hu *et al.*, 2017b; Liu and Zhu, 2017; Lu *et al.*, 2013; Yan *et al.*, 2014a) whereas deep feature learning are used in (Li *et al.*, 2016; Li *et al.*, 2017; Zhou *et al.*, 2019). For example, Lu *et al.* (2013) proposed neighbourhood repulsed metric learning (NRML) method that utilizes a single feature and metric with a view to learn a distance metric under which samples (positive kin relations) are pulled as close as possible and samples (negative kin relations) are pushed away as far as possible simultaneously, such that more discriminative information can be utilized for recognition. However, because the less of discriminative information that uses to characterize face images, the method failed to learn the distance from the single feature space, and hence producing insufficient results.

Further to that, metric learning methods such as multiview NRML (MNRML) (Lu *et al.*, 2013), discriminative multi-metric learning (DMML) (Yan *et al.*, 2014a), large-margin multi-metric learning (LM^3L) (Hu *et al.*, 2017b), discriminative deep metric learning (DDML) (Lu *et al.*, 2017), structured sparse similarity learning (S^3L) (Xu and Shang, 2016a), and weighted graph embedding based metric learning (WGEML) (Liang *et al.*, 2018) that are based on jointly utilize the complementary information from multiple features representations to learn and obtain multiple discriminative metrics in order to deal with multiview data. The results of such methods are limited since they learn a linear distance metric for input space, which is less powerful to capture the non-linear transformation. Besides, these methods which are based on handcrafted feature are suffer from different factors like physical appearance variance. In addition, deep feature learning needs a large number of labeled training data to find the best representation of face images (Najafabadi *et al.*, 2015), and thus more flexible metric model.

However, metric learning methods have a limited precision reliability because it is incapable to accurately understand semantics of kin relationship. In addition, metric learning requires very large training data especially with deep neural networks (Zhou *et al.*, 2019). Moreover, in kinship recognition domain, most of the existing methods have intensively focuses on the choice metric learning while overlooking the prominent facial features that indicates the kin relation (Duan *et al.*, 2017a; Goyal and Meenpal, 2019; Li *et al.*, 2016). Likewise, choose a proper metric to learn distance is difficult, as a rigid distance measure such as Euclidean distance has no ability to mining the substantial and stable underlying face image's structure for performing kinship recognition (Liang *et al.*, 2018). Furthermore, it mostly use entire image globally to describe the visual content and generated features which is sensitivity to the facial appearance change like illumination and pose variances (Kabbai *et al.*, 2019), may failure to capture other substantial information that has different semantic meanings about kinship (Kamila, 2015), need large amount of data to generate learning patterns and confront the environment variations conditions like illumination (Qin *et al.*, 2020; Zhao *et al.*, 2019), and also not suitable for handling intra-class variations (the difference of face image pairs with kin relation) (Wu *et al.*, 2010).

Typically, two major components, namely, face representation and matching are crucial importance stages to kinship recognition (Fang *et al.*, 2016; Liang *et al.*, 2018). Face representation focuses on describing and mining distinctive features from face images, while matching concentrates on developing effective models uses extracted features to compare and classify face images. However, the facial features extraction is an indispensable process of the kinship analysis. The idea of selecting and utilizing dynamic features for determining kinship is considered a significant challenge (Dornaika *et al.*, 2020) as it strongly influences decision-making performance. The most frequently underlying causes related to identifying the prominent cues for kinship may back to various reasons, as follows:

First, reported results showed that the face recognition methods may fail to train model if only using one training image per person (Tan *et al.*, 2006). Similarly, a single image per person is not enough to well represent a familial traits either because the variations of illumination and pose, or lost useful information from the image in order to explicitly handle kinship problem (Li *et al.*, 2017; Xia *et al.*, 2018). However, most of the reviewed methods of kinship strongly depends on learned and extracted general features representation from a single source of image, where the multiplicity images per person was overlooked. Therefore, the precise features of structural kin-relationship meaning cannot be disclosed as well as decision on which of them are important for recognizing kinship is difficult. In this regard, the leverage of utilizing multiple images associated with the same person can enhance the reliability of kinship similarity and recognition.

Second, the strong relevance cues of kinship are limited to specific facial parts, including eyes, nose and mouth (Georgopoulos *et al.*, 2018; Patel *et al.*, 2017; Xia *et al.*, 2012b). However, the idea of restricting certain regions or even specifying those parts in advance to determine kinship is a sensitive and will affects the generalization ability, because kin can have strong or weak similarities of specific facial parts. For example, the eyes of a daughter can be similar to the eyes of her mother, but can be dissimilar to the eyes of her father, in which the similarities vary from an individual to another, thereby complicates the kinship analysis process. Further, two people from one family likely have a fair number of attributes sharing, yet may do not resemble each other, whereas individuals with no attributes sharing may look closely resemble (Laiadi *et al.*, 2019b). However, the existing methods that have been proposed for kinship recognition by using multiple face region features are producing insufficient results. For example, (Guo and Wang, 2012; Van and Hoang, 2019a) noted that the results of such methods are controlled by specific facial parts, which are unable to locate the signs of kinship thus less capability of modelling kinship recognition system.

Third, as mentioned above, as focusing on specific pre-defined local parts of the face is ineffective, likewise, utilize every local parts of the face to shape the final feature representation is not helpful (Cui and Ma, 2017) which will drive to select unnecessary part(s) that do not have semantic features indicating kinship. Moreover, the majority of current methods considered all the local parts of facial image equally in detecting the kinship, where single or multiple features are extracted from every part are then concatenated together directly into a new feature vector. However, this process is meaningless because each feature and part has its own characteristic and hence cannot effectively discover the complementary information (Cui and Ma, 2017). In addition, ignore those features and parts that are might to be correctly classified or misclassified in order to recognize kinship. All of these concerns result in generate unwanted redundant and information, high dimension of features, and reduces performance (Alirezazadeh *et al.*, 2016).

Fourth, in image-based kinship analysis, fusing multiple feature representations is desirable to provide more discriminative and complementary information to describe face image, hence revealing the underlying kinship cues, increasing the learning capability and likely improving the overall performance (Bottinok *et al.*, 2015; Dornaika *et al.*, 2020; Lu *et al.*, 2013; Yan and Lu, 2017a). The outcome is high-dimensional feature vector that may contains redundant, irrelevant and noisy information (Alirezazadeh *et al.*, 2016; Van and Hoang, 2019a). Additionally, the parent-child images comprise many details that include inherited and environmental information, and other more, so it should only pay particular attention to the genetically inherited transmitted information. However, learning becomes significant inconvenient, increases computational complexity, more resources would be needed for processing, and overfitting problem (Zhao *et al.*, 2018). Hence, the necessity of dimensionality reduction technique increases. In kinship recognition domain, feature space high dimensionality is a common problem (Alirezazadeh *et al.*, 2015; Alirezazadeh *et al.*, 2016; Duan and Tan, 2015; Moujahid and Dornaika, 2019), which aim to get rid of the useless and unrelated features in order to improve the performance. The aim of feature selection is to get rid of the useless features from the defined features set, resulting the reduction of the dimensions of feature vector. Nevertheless, dimensionality reduction techniques can achieve promising results to resolve the high-dimensional features and improve computational intensive, yet, might lose some of the useful and distinctive cues information (Alirezazadeh *et al.*, 2016; Guo *et al.*, 2018), which could failure identification of cues about kinship, and thus cause difficulties on recognizing kinship.

Fifth, the determination of kinship information based on facial images will be further complicated under uncontrolled environments especially when the database has limited number of images, which makes the problem of kinship even more challenging. However, some of the face-based kinship recognition problems are inherited from the conventional face recognition domain issues including large diversity of facial appearance such as variations of illumination, pose, partial occlusion, facial expression, low resolution images and blur, besides inter-class similarities and the intra-class variations. It's also suffer from other factors like age gap, gender and ethnicities variations, and others (Akhtar and Rattani, 2017; Dandekar and Nimbarte, 2014; Georgopoulos *et al.*, 2018; Laiadi *et al.*, 2019b; Li *et al.*, 2016; Li *et al.*, 2017; Wu *et al.*, 2016a; Yan and Lu, 2017a). For example, the results of the previous works present some interesting consensus view on the problem of the aging effects (Laiadi *et al.*, 2019b; Lelis, 2018; Liu and Zhu, 2017; Xia *et al.*, 2011; Zhou *et al.*, 2019), which should be taken into account when dealing with automatic kinship recognition. Consequently, in such circumstances, the implicit familial traits may not be adequately represented. Thus, the kin-relationship exact features extracting is still a very challenging task.

Therefore, feature extraction and learning strategy are of vital importance, which also are desired for achieving accurate recognition results. Accordingly, in order to enhance the effectiveness of determining the set of physical characteristics that can highlight relevant information closely associated to a specific pair of face, methods of the kinship recognition should be developed, which have the power to learn and extract more abstract and reliable resemblance patterns of kin samples from images.

1.3 Research Aim

The aim of this study is to develop enhanced methods for identifying, tracking, and extracting the visual similarity of familial features correlated with detecting kinship via facial images in order to improve the performance of the kinship verification.

1.4 Problem Statement

The development of an accurate computational system for kinship recognition crucially depends not only on the extraction of discriminative facial feature representation that represent the content of the face image but also on the design suitable matching scheme and learning methods applied (Fang *et al.*, 2016; Liang *et al.*, 2018).

The kinship recognition becomes more challenging since the familial features have own properties for each certain pair of family members (Guo and Wang, 2012), the cues information that provide evidence for kinship are still remain unknown (Alvergne *et al.*, 2007; DeBruine *et al.*, 2009). In addition, facial resemblance between one family members could be found in different facial parts, which is also seems differently across various families (Lopez *et al.*, 2018). This shows that perceiving the decisive clues of kinship is ambiguous and vulnerable to instability, thereby cannot be easily revealed under the ordinary methods (Zhao *et al.*, 2018). Besides, attempting using the same parts or features to determine the kinship among people is probably exposed to failure, because there is no general rule of the similarity's features can be generalized to all facial pairs or relationships types (Lopez *et al.*, 2018). Moreover, on account of less amount of similarities among family members, a single image per person may not be informative enough to extract the precise familial traits, which leading to inaccurate measure of kin relation. This essentially needs adopting additional images to utilize further complementary information of the given person in order to improve the generalization ability.

Furthermore, considering the following problems: 1) lack of evidence about which the specific part(s) of image can provide indication regarding kinship, 2) the difficulty to disclose the whereabouts of kinship signals and making a decision on which part(s) are important, and 3) with the assumption that not all regions of an image is useful to determine the kin relation, thus it is possible to obtain irrelevant and inaccurate information of kinship clues when using either or both of multiple images and local parts which resulting false matched kinship. Therefore, utilizing a singular classifier performs less well to make decision of recognizing kinship as compared to considering combined several classifiers developed cooperatively to form a robust model, where combines the decision of multiple classifiers can be more stable, helpful to reduce the error in classification by eliminating falsely matches (outliers removal), and the truly matches are only considered, also reduce model variance and bias, and hence improve the overall accuracy performance (Kim *et al.*, 2006; Moreno-Seco *et al.*, 2006; Tsai and Hsiao, 2010).

By awareness and comprehension of the problem background and problem statement which have been discussed previously, the methods attempt to discover and utilize the familial resemblance information extracted from facial images to be able to perform kinship recognition. However, the traditional methods of kinship still suffer from low accuracy, further works are still required to design new methods for the domain of kinship. Therefore, this research raises various challenges, such as minimize the recognition errors to improve the accuracy and enhance the tracking the most fitting cues of the physical similarities shared between people for determining the kin relationships.

The following section puts forward the research questions (RQs) that will be further investigated in this research study.

1.5 Research Question

This research proposes enhanced familial features to measure kin relationships between individuals and between families through facial image for robust kinship verification. The main research question is:

"How the familial resemblance features can be determined and extracted from the facial images, and utilized in order to develop enhanced methods for the effective performance of kinship verification?"

Moreover, the following are the research questions (RQs) that will need to be investigated in order to answer the main research question stated above.

(a) What are the current kinship recognition approaches and feature extraction methods that capable of describing the visual resemblance information well besides achieving better performance for the face-based kinship recognition?

(b) How to utilize deep learning convolutional neural network (CNN) improve the performance of kinship recognition?

(c) How to incorporate the facial images of parent and children into one matrix representation, and eliminate redundant, unwanted and noisy information for efficient kinship recognition?

(d) How can the integration of all the useful feature sets extracted from several important local parts of image while removing irrelevant local parts generate a better performance in kinship recognition system?

(e) How can utilize multiple images and different representations per person to produce complementary information and effective familial features than that provided by a single image to improve the performance of the kinship recognition model?

(f) How can utilize fusion technique to combines the outputs of multiple classifiers into a single decision to improve the performance of kinship recognition?

(g) Do the kinship recognition models based on the proposed methods yield significant results?

1.6 Research Objectives

This research introduces new methods to develop high-accuracy computerized models, with ability to improve the quality and effectiveness of image-based system of kinship verification. However, kinship verification seeks to verify whether there a specified kind of kinship between pair of individuals based on given facial images by measuring features similarities extracted from these facial images.

The objectives of this research have been set as follows:

i. To develop an enhanced method based on incorporate parent and child information into new matrix representation using local raw pixels similarity, and convolutional neural network.

ii. To propose an enhanced fusion feature method based on the best familial feature of different overlapping facial blocks that would be capable of improving the verification accuracy.

iii. To propose an ensembling method based on selecting best combination of different augmented image representations that consider the selection of the best combination sets besides utilizing Siamese convolutional neural network that would be capable of achieving better performance than individual image representation methods.

1.7 Research Scope

The following aspects are the scope of this research study:

i. This research focuses on faces taken from images, so the contents of other multimedia types such as videos are out of this research scope.

ii. This research is concerned with two well-known task including image-based kinship verification (the definition has been mentioned in Section 1.6), thus other tasks such as kinship identification are out of this research scope.

iii. This research focuses on three popular databases, namely, KinFaceW-I and KinFaceW-II (Lu *et al.*, 2013) databases for kinship verification where all images have been considered.

iv. This research is using the popular machine learning algorithms including convolutional neural network (CNN) (O'Shea and Nash, 2015), support vector machines (SVM) (Zoppis *et al.*, 2019) and artificial neural network (ANN) (Rojas, 2013) as classifiers for kinship verification.

v. This research focuses on the common evaluation metric, i.e., accuracy (ACC) to be used to measure and evaluate the proposed methods, however, the most common evaluation protocol, i.e., k-fold cross validation, especially 5-fold cross validation will be used in this study.

vi. This research has been implemented in the Keras API (Chollet, 2015) (version 2.2.4) which is an open source deep learning library running on top of TensorFlow (version 1.14.0) using Python (version 3.7.6) programming language.

vii. The methods proposed in this research concentrates on achieving higher level of accuracy performance, thus, the complexity analysis of these methods is beyond the scope of this study.

1.8 Research Significance

So far, the deoxyribonucleic acid (DNA) is considered most reliable and popular testing method to determine biological relationship between people with highly accurate result. In place of direct DNA comparison, recently, a new powerful identification tool known as genetic genealogy (GG) (Bettinger, 2019; Kennett, 2019; Ney *et al.*, 2020) which also known as relative matching (Ney *et al.*, 2020), is genealogical DNA tests uses to analysis and predict the family genealogical details using genetic information.

Practically, however, utilizing DNA is very limited, for reasons related to the time that takes for processing which is not suitable for the real-time applications, high cost, privacy concerns and accessibility. All these reasons have turned the researchers to looking for an alternative solution to measure the genetic similarities and kin relationship among people. However, the human face can be the typical solution to provide clues about kinship, due to the following reasons: face is the most widely method used to identify people, obtaining an image effortlessly and mostly, does not requires a user cooperation, inexpensive to implement due to the availability of resources, suitable for the real-time applications, and user friendliness.

Motivated by these discoveries, the biological relationship and similarities between family members inspire researchers to develop a computer-based system that will be able to automatically recognize kinship based on the facial image. Recognizing people and their relationship has significant social, security and business values.

One of important application of kinship recognition system is finding missing children. In this case, most often, there are several common ways for this task, such as description, DNA and photograph. In fact, find a missing child among millions of children is costly and time consuming. However, the easiest, faster, inexpensive and most widespread way which can cover large-scale maps, is using the visual resemblance based on face image that passes to a computerized kinship recognition system operating on the basis of machine learning and advanced artificial intelligence.

Another possible application of kinship recognition is forensic investigation. The security, fighting against crimes, and countering terrorism are extremely important to the safety and preserve societies. To the best of authors' knowledge, most countries have records of citizens and residents, suppose that a person committed an offense, but unluckily does not have a record file in the database. In this scenario, therefore, the interrogators could go forward and searching for all possible signs of kinship between the person who committed the offense and the rest of individuals contained in the database. In the other words, search for all the potential relatives in the database (Slooten and Meester, 2012). However, automatic recognition of kinship is essential for many potential real-world applications (Robinson *et al.*, 2016a, 2016b; Wang *et al.*, 2020c), for example, family tree and album organization, automatic management and labeling/annotation of image databases, image retrieval, social media analysis, historical and genealogical research, finding missing children, human trafficking, and forensic science. Moreover, models of the kinship recognition could be utilized to further improving the performance of facial recognition systems.

The aforementioned motives and applications attract a significant number of researchers to present their contributions in this area. Evidently, research in this domain is still active and evolves dramatically. The face image-based kinship model development process and the necessity of understand visual similarities and discovering discriminant representations for building a system for detecting biological relationship (kinship) between people, the reason to form the cornerstone for the work given here. It is firmly believed that identifying powerful familial features can improve and help the fully automated kinship recognition system development process. The significance behind conducting this PhD research study is to propose new state-of-the-art and advanced methods for the recognizing kinship via facial image. In view of the aforementioned issues, the results of this research study will contribute not only to knowledge enrichment, but also to more detailed understanding about kin relationship and how to reducing the recognition errors and improving kinship recognition. Although inherent complexity of kinship problem, which dealing with many severe issue challenges, however, the results also contribute the effective solutions to these challenges can be successfully developed and implemented within an appropriate technique framework.

1.9 Thesis Structure

This thesis comprises of seven chapters, which includes:

Chapter 1: this chapter presents a general introduction to the topic of the research work. This chapter also includes a brief overview of some of the issues and challenges concerning the research. In addition to the problem background and problem statement, besides the research aim, objectives, scope, significance of the study, and finally, the organization of this thesis.

Chapter 2: this chapter gives a review of related literatures of kinship recognition studies. The chapter introduces the fundamental concepts related to kinship recognition, such as the definition, systems of verification and classification, relationship with the identity recognition, major characteristics and challenges. Then, it discusses the significant efforts of psychology studies which have been put to comprehension of human ability to recognize kinship and provides the explanation and fundamental concepts related to it. Also, this chapter also covers the basic approaches of designing an automated computer-aided kinship recognition system. Moreover, reviews and discusses other details related to the current study, such as feature extraction methods, information fusion methods, common machine learning algorithms, and later, the chapter presents the deep learning techniques, particularly convolutional neural network (CNN).

Chapter 3: this chapter presents the research operational framework used in this research. It consists of the methodology of the research and the steps in all phases required to proceed with the research systematically. Furthermore, this chapter introduces discussion of the research components, such as the phases, classification method, evaluation protocol, and performance evaluation measurements. Finally, the kinship database and the experimental design are presented.

Chapter 4: in this chapter, the convolutional neural network (CNN) based on optimized local raw pixels similarity representation (CNN-OLRPSR) method for kinship verification has been explained in detail, that would capable of eliminating redundant information and reduce the dimensions of the feature space. This chapter includes the description of a new matrix representation based on non-overlapping local block that incorporate the pixels information of parent and child images, the architecture of deep convolutional neural network model for feature extraction and classification, the similarity measurement techniques, and the experimental setup. The details of the method steps and other procedures, are further discussed in this chapter. Finally, the results of CNN-OLRPSR method using the adopted databases are reported, compared, and discussed, also in this chapter.

Chapter 5: in this chapter, the method of fusion of the best familial feature of different overlapping facial blocks (FBOB) along with Siamese convolutional neural network (SCNN) to formulation of a new SCNN-FBOB method for kinship verification has been discussed in detail. The experimental results of SCNN-FBOB method on adopted databases are presented and discussed. The details of the method steps and other procedures, are further discussed in this chapter. Finally, the comparison between the performance of SCNN-FBOB method, on one hand, and the CNN-OLRPSR method and previous state-of-the-art studies performance, on the other hand, is highlighted.

Chapter 6: this chapter explains the ensembling method based on selecting best combination (EMSBC) using different augmented image representations, constructed on Siamese convolutional neural network (SCNN) in the form of SCNN-EMSBC for kinship verification. This chapter describes the image-based kinship verification using the several image representations in the SCNN model, and examines the performance of every image representations, individually, and the different possible combinations subsets are also examined. Additionally, it also includes the information fusion technique, artificial data augmentation, and the procedure of combination generator. However, the detailed explanation of the method steps and other procedures, are discussed extensively in this chapter. Finally, the experimental results of SCNN-EMSBC method on adopted databases are presented, and the comparisons with the performance of CNN-OLRPSR method, SCNN-FBOB method, and previous state-of-the-art studies, are also shown.

Chapter 7: this chapter provides the conclusions and findings of the study discussed throughout this research work. The chapter also highlights research contributions and future work suggestions.

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