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Thème

FACE BASED AUTOMATIC KINSHIP VERIFICATION

Soutenu le 26 /06/2021

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إهداء

الحمد لله رب العالمين والصلاة والسلام

على سيدنا محمد أشرف المرسلين

وعلى آله وصحبه أجمعين .

أهدي ثمرة جهدي

إلى من أحب بسمتي وتعب لراحتي , وهو مفتاح صبري

وسر هنائي أبي العزيز

إلى من هي أرق من النسمة وأطيب من العطر "أمي"

حفظهما الله لي

إلى منبع اعتزازي وسندي في الحياة "إخوتي"

إلى من شاركني هذا العمل "صديقتي"

إلى كل من عرفناهم وسعتهم قلوبنا ولم يسعهم قلمنا . . .

سمية, منيرة, إيمان....

شكرا وعرفان

بداية نتوجه بالشكر الجزيل وإلى المولى تعالى الذي أنعم علينا بهذا وأعاننا

على إنجاز هذا البحث ووفقنا فيه وإليه يرجع كل

الفضل .

كما نتقدم بالشكر الجزيل والتقدير إلى كل من ساعدنا

في إنجاز هذا العمل ونخص بالذكر الأستاذة الدكتورة "أمينة التجاني" التي أفادتنا

بنصائحها وإرشاداتها القيمة وكانت

سندا لنا . كما نتقدم بالشكر الجزيل إلى كافة الأساتذة والدكاترة

في قسم الهندسة الكهربائية' اللذين أفادونا بنصائحهم وتوجيهاتهم العلمية ودعمهم

المعنوي حتى نهاية هذا المسار

البحثي ونسأل الله أن يبارك هذا العمل وليجعله خيرا للبحث العلمي

وأن يوفقنا إلى ما فيه خيرا وصلاحا لنا .

Abstract

Face based automatic kinship verification is a novelchallenging researchproblem in computer vision. It performs the automatic examining of the facialattributes and expecting whether two persons have a biological kin relation ornot.

This work focus on kinship verification based feature extraction task. Wepresented an original investigationto detect the most significant characteristicfeatures of human faces and it should help from the improved performance ofkinship verification.

Mots-clés: biométrique. parenté. verification.

Résumé

La vérification automatique de la parenté basée sur le visage est une nouvelle recherche stimulanteproblème de vision par ordinateur. Il effectue l'examen automatique du visageattributs et attendre si deux personnes ont une relation de parenté biologique oune pas.

Ce travail se concentre sur la tâche d'extraction de caractéristiques basée sur la vérification de la parenté. Nousa présenté une enquête originale pour détecter la caractéristique la plus significativecaractéristiques des visages humains et cela devrait contribuer à l'amélioration des performances devérification de la parenté.

Mots-clés : biométrique. parenté. vérification.

ملخص

التحقق التلقائي من القرابة القائم على الوجه هو بحث جديد مليء بالتحديات مشكلة في رؤية الكمبيوتر. يقوم بإجراء الفحص التلقائي للوجه الصفات وتوقع ما إذا كان شخصان لديهما علاقة بيولوجية قرابة أو لا .

يركز هذا العمل على مهمة استخراج الميزات القائمة على التحقق من القرابة. نحن ن قدم تحقيقًا أصليًا للكشف عن أهم خاصية ملامح الوجوه البشرية ويجب أن تساعد من تحسين أداء التحقق من القرابة.

الكلمات المفتاحية: بيومترية . القرابة . التحقق.

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Abbreviations

CA-LBFL : Context-Aware Local Binary Feature Learning

DFD :discriminate face descriptor

CBFD : compact binary face descriptor

PDV :pixel difference vectors

LBP : Local Binary Patterns

LPQ : Local Phase Quantization

LDA : Linear Discriminate Analysis

PCA : Principal Component Analysis

ROC : Receiver Operating Characteristic

NN : Nearest Neighbor

SVM : Support vector machines

LML: Local Large Margine Multi Learning

IML:IndividualMetric Learning

GSML:Generalized Sparse Metric Learning

Géneral Introduction

In today's networked world, the need to maintain the security of information or physical property is becoming both increasingly important and increasingly difficult. From time to time we hear about the crimes of credit card fraud, computer breaking’s by hackers, or security breaches in a company or government building. the criminals were taking advantage of a fundamental flaw in the conventional access control systems: the systems do not grant access by "who we are", but by "what we have", such as ID cards, keys, passwords, PIN numbers, or mother's maiden name. None of these means are really defining us. Rather, they merely are means to authenticate us. It goes without saying that if someone steals, duplicates, or acquires these identity means, he or she will be able to access our data or our personal property any time they want. Recently, technology became available to allow verification of "true" individual identity. This technology is based in a field called "biometrics". Biometric access control are automated methods of verifying or recognizing the identity of a living person on the basis of some physiological characteristics, such as fingerprints or facial features, or some aspects of the person's behavior, like his/her handwriting style or keystroke patterns. Since biometric systems identify a person by biological characteristics, they are difficult to forge. Among the various biometric ID methods, the physiological methods (fingerprint, face, DNA) are more stable than methods in behavioral category (keystroke, voice print). The reason is that physiological features are often non-alterable except by severe injury. The behavioral patterns, on the other hand, may fluctuate due to stress, fatigue, or illness. We therefore devoted our study to one of these few biometric methods that have the advantages of high accuracy and low intrusion in the field of face kinship verification, which is one of the main topics in image processing, computer vision and pattern analysis. In the few decades the problems of facial verification and people recognition have been a focus of great interest and digital images are shared across many media platforms. The potential relationships in the images include those between relatives, colleagues, and friends. In addition, biological relationships and similarities between traits in the same family inspire us to take advantage of this fact to develop a computer system that is able to recognize kinship faster and more accurately.

Facial kinship verification is a module aiming to analyze pedigree construction and calculate similarity indices for different facial traits. This problem has several interesting applications, such as family album organization, finding missing children and social media it still challenging for real applications because there are usually large variations in pose, expression, illumination, age, ethnicity, especially, when face images are captured in unconstrained environments[5].

In this thesis, we focus on using computer vision techniques to automatically detect the relationships between two persons from their faces.

The main points of this study are highlighted in the following context:

First, the most important challenge is how to describe a face, and how to recognize it the different facial features of children, and then how to relate them to the corresponding parents without being affected by different challenges.

We propose an effective Context-Aware Local Binary Feature Learning (CA-LBFL) for kinship verification. The CA-LBFL is a method has applied to learn contextual features from raw pixels directly and to eliminate the dependence on hand-crafted features.

1.3 Thesis Organization

The rest of thesis is divided as following:

Chapter 1,details the facial kinship verification task. We give an overview of automatic kinship verification from faces by presented some notions, definitions and terminology required for understanding this topic. Next, we describe the system design of facial kinship verification. The chapter presents also some applications and the challenges related to facial kinship verification. Finally, we summarize some existing databases.

Chapter 2, the features extraction and classification method used for the kinship verification are discussed in detail in this chapter. we present one method based on learned (No Hand-Crafted) features learning, we propose a context-aware local binary feature learning (CA-LBFL) method for face recognition. with method Feature Selection (FS) which a data preprocessing step that is applied after feature extraction step. Feature selection method aims to select the most relevant subset of extracted features to provide a useful classification with the smallest error and to discard non-relevant features, the specific feature values are computed using feature normalization (z-score) and classification can be performed with a linear classifier If the extracted face features are discriminative enough, . The metric learning methods aim to seek an appropriate distance metric for classification tasks and have achieved a good performance in many facial image analysis applications. The Cosine function is used to calculate the Similarity or the Distance of the observations in high dimensional space, and we finally remember Cross-validation, It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice.

Chapter 3, experimental results of facial kinship verification analysis are presented and discussed. We have investigated the kinship verification task using an effective method called CA-LBFL. The CA-LBFL is a method has applied to learn contextual features from raw pixels directly and to eliminate the dependence on hand-crafted features.

Chapter 01:

Facial Kinship Verification

1.1Introduction

Biometrics is a study that assesses a person's personality based on physical, physiological, and anatomical features. It includes the ability to automatically identify people's identities based on their physical, physiological, and anatomical features. This proof surpasses fingerprints as well as the comfort of the palms and feet. Each person's uniqueness refers to their individuality, and computers can match them in seconds using distinctive signs and points, as well as identification through the voice, pupil of the eye, or facial features, because these members are distinguished by their uniqueness in each person, such as fingerprints and the palm of the hand and feet.

As a result, we'll look at the face recognition system, which is a technology that can automatically identify or verify a person in a digital image or a video frame obtained from a video clip. Facial recognition systems function in a variety of ways, but they all operate. In general, it matches the specified facial traits in a snapshot to the faces contained in the database.

1.2Meaning of kinship

Before we delve into studying, we must be familiar with the different terminology of kinship. Kinship plays an important role in social network analysis. As a special type of social relationship. Kinship is term that has several meanings in general, such as similarity and intimacy, and it is a word used to identify the degree of genetic connection between two numbers of the family. Kinship in psychology is the state of connection with birth, common descent, adoption, or marriage in an anthropological context. Kinship is a network of social relationships between people that constitute a large and important part of the life of most societies, and to assess children’s relationships with parents based on the similarity of signs between them, and to identify the child’s lineage by looking at this body parts and those of his parents in this way, different societies classify kinship relationships differently and thus use different systems of kinship meanings and terminology.

1.3Kinship in computer vision

Kinship verification has also gained interest in the computer vision and machine learning communities. The first dataset containing kin pairs was collected by *Fang et al*. [6]. For performing kinship verification, the authors proposed an algorithm for facial feature extraction and forward selection methodology. Since then, the algorithms for verifying kin have increased in complexity [2]. Computer vision, verifying identity and recognizing kinship is a difficult problem, with different facial effects such as changing facial expressions, make-up, and aging. In addition to the difference in age and age these complication characterize the field of automatic identification of kinship as a broader and more difficult problem than traditional face verification and identification. Basically, the problème are dividedintotwoparts:

1. The direct challenge related to the kinship itself.
2. The indirect challenge related to the database environment.

While existing algorithms have achieved reasonable accuracies, there is a scope of further improving the performance.

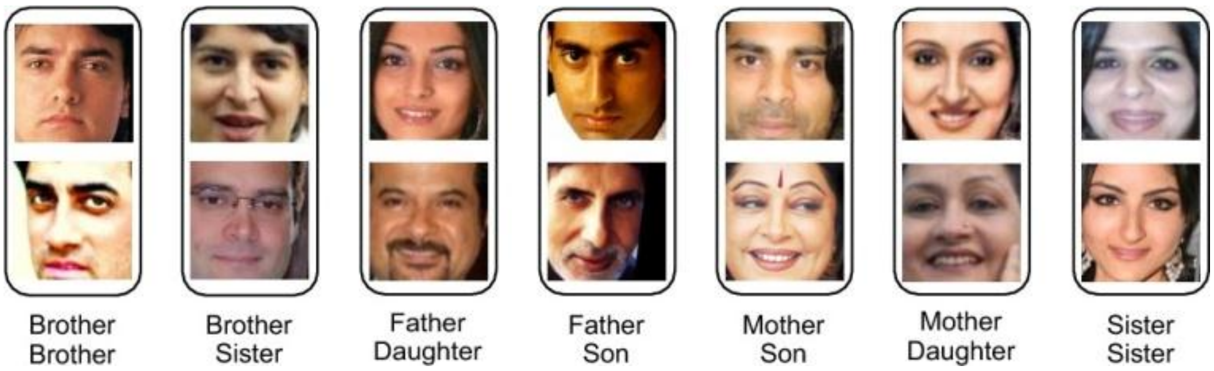


Fig. 1.1. Examples of kin-relations considered in TSKinFace[2].

1.4 Face Verification and kinship verification

Face verification is the process of matching a group of faces or two sides together, the goal of which is to verify the correct person, in other words the task of comparing a candidate's face with anther face and verifying whether they are identical or not. Verification of kinship is a comprehensive study aimed at verifying the kinship of individuals and the relationship between them. It has many methods, including the method of verification by face. That is verification of kinship and verification of the face are two different matters among themselves, but they have basic evidence that is the common factor between them.

The basic structure is the common factor between kinship verification and face verification system and the differences between the facial and kinship verification is shown in Table 2.1.

Table 1.1: Difference between kinship and face verification system.[7]

Facial verification	Kinshipverification
Extractfeaturesfromsameperson	Verify the relationships
Verify or identity	Different trait of query image 1and queryimage 2
Same trait of query image1 and query image2	Highestlevel system
Heightlevel system	Studying the biologicalrelationshipand utilizes by people and les by governmentagency
The mostcommon application is the security, monitoring and extensively by government a agencies	In decision stage kin or not kin

1.5 System design

Automatic kinship detection using facial photographs is a difficult subject that has lately attracted the interest of computer vision and pattern recognition researchers working on social communication. Kinship is a genetic connection between two family members. We distinguish between four forms of kinship relationships: mother and daughter (M-D), father and daughter (F-D), mother and son (M-S), and father and son (F-S) [1].

The kinship verification has been studied. The findings from the include that:

• Human faces can convey some important cues to identify the kin relations of persons.

• Humans are able to recognize kinship relationships between unknown individuals.

• The mechanism of kinship perception is probably different from identity recognition.

• Even attempted to identify the facial features providing kinship clues.

Figure **1.2:**KinFaceW-II database. Four type relationships: (F-S), (F-D), (M-D),and (M-S).

• Facial appearance is a useful cue for genetic similarity.

Human faces have abundant features that explicitly or implicitly indicate the family linkage, giving rich information about genealogical relations. We address the novel challenge by posing the problem as a binary classification task, and extracting discriminative facial features for this problem. Our method works according to the following steps:

Step 1: Parent-child database collection.[8]The facial image database of parent-child pairs is collected through a controlled on-line search for images of public figures and celebrities and their parents or children. We collected 150 pairs using this method, with variations in age, gender, race, career, etc., to cover the wide distribution of facial overview of the facial image database collected.

Step 2: Inherited facial feature extraction. [8] We start with a list of features that may be discriminative for kinship classification (such as distance from nose to mouth or hair color). We first identify the main facial features in an image using a simplified pictorial structures model, then compute these important features and combine them into a feature vector.

Step 3: Classifier training and testing. [8] Using the extracted feature vectors, we calculate the differences between feature vectors of the corresponding parents and children, and apply K-Nearest-Neighbors and Support Vector Machine methods to train the classifier on these difference vectors, as well as a set of negative examples (i.e., image pairs of two unrelated people) The final outputs provide two different types of information: the most discriminative facial features for kinship recognition and trained classifier to differentiate between true and false image pairs of parents and children.

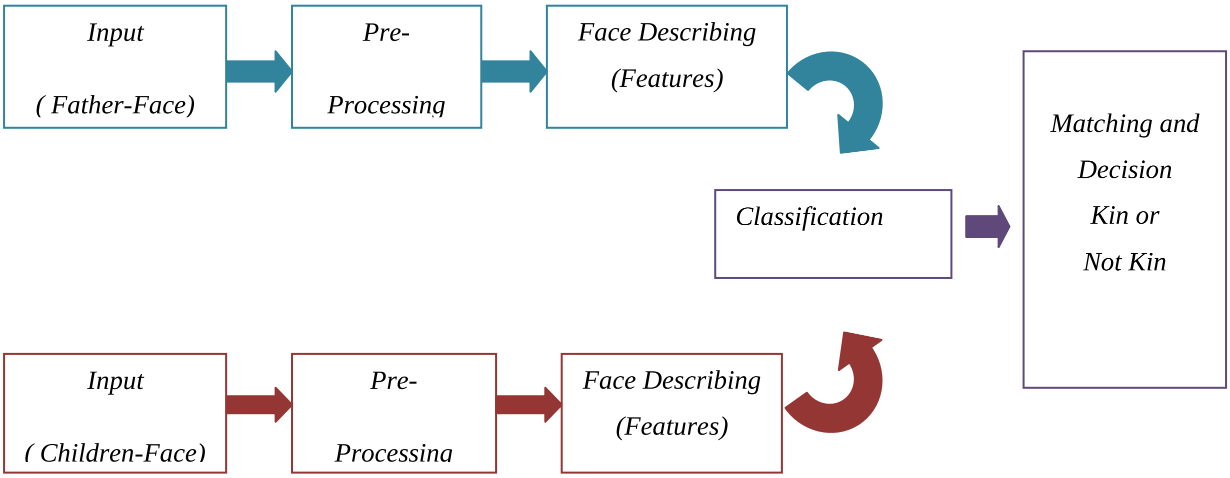


Figure1.3: General schema of kinship verification system[7].

Input (face datasets): includes public figure face images of family members collected from the Internet. Therefore, the face images are captured under uncontrolled environments with no constraints.

Pre-processing: is an important component. In order to localize the face of the image, this latter is then cropped, such that the non-facial regions such as the background and hairs were removed and only facial region was used for kinship verification. If those are color images, they converted into gray-scale images. For each cropped image, histogram equalization was applied to mitigate the illumination.

Face describing: the best way to learn kinship analysis is first to learn how to recognize the different facial features for children, and then learn how to relate them to their corresponding parents. Facial features must be described in a way that enables them to be efficiently descriptors.

Classification and Decision: kinship Verification is bi-classification problem where the pair of input faces is classified as positive (the true pairs of parents and children) or negative (the false pairs of parents and children).

1.6 Application

Face recognition has become more significant, active, and widely applied in current real world situations. With the technological advances, such as high-quality digital cameras, mobile devices, and the Internet, the digital images are becoming a new identity marke of a person. Thus, the study of kinship through faces has become an interesting subject with great scientific importance. It has a great impact on real application and many fields [9].

We summarize the possible areas of application as follows:

- ✓ Historical and genealogical research
- ✓ Forensic science
- ✓ Finding missing family members
- ✓ Trafficking/smuggling of children
- ✓ Social media analysis
- ✓ Automatic management and labeling/annotation of image databases
- ✓ Identifying relatives from a photo collection and image retrieval
- ✓ Building a dynamic relation tree from photos and family album organization

1.7 Kinship problems and challenges

In fact, to obtain an effective solution to the kinship problem, we must initially determine the problems and challenges that hinder the achievement of the ultimate goal, which will help us to understand the problems and supply a guide to develop a system to identify kin relationship automatically. Complications emerge because of variations in age, gender illumination, pose, or minimal similarity between distant kin. These complications characterize the field of automatic kinship recognition as a broader and more difficult problem than traditional face verification and identification. Fundamentally, the problems are divided into the following two categories: (1) directly challenging (related to kinship itself) and (2) indirectly challenging (related to the environment of the database). With respect to the directly challenging problems, many earlier studies have identified four substantial issues [6, 10, 11, 12], namely, (i) verifying feature resemblance between kin, (ii) verifying the existence of kinship, (iii) identifying the exact type of kin relationship, and (iv) variations in age and gender.

1.8 Databases

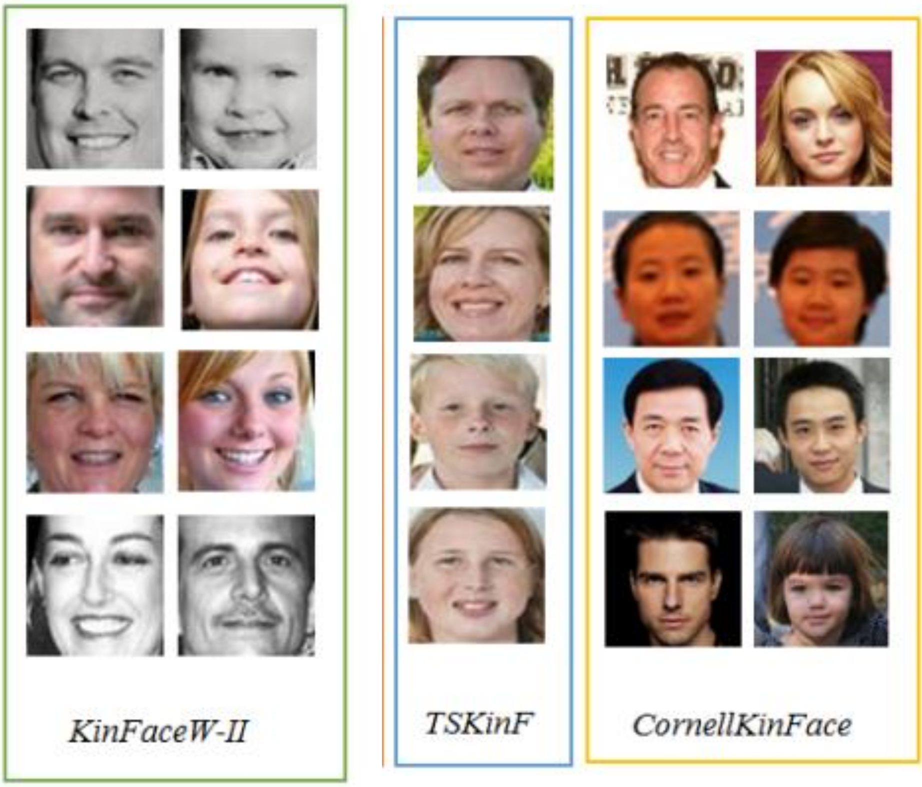
To evaluate the performance of the proposed kinship verification technique, we considered three kinship databases: Cornell Kinship database, TSKinFace database and KinFaceW (I & II). These databases consist of four kinds of parent-child relationships. The face images are with various ages and ethnicities, and captured under uncontrolled environments and no restriction in terms of pose. In the following, a brief description of the databases is given.

Cornell kinship database [13] contains 143 pairs of parents and children images collected from the Internet. In total, there are 286 cropped frontal face images of size 100×100 pixels. The majority of the images were taken from Google Images. To make sure that the facial extracted characteristics are of high quality, only frontal face images with a neutral facial expression are chosen. We note that, for privacy issue, 7 families are taken out of the original database that consists of 150 families.

TSKinFace database [14] contains two kinds tri-subject kinship relations: Father-Mother Daughter (FM-D) and Father-Mother-Son (FM-S). The number of FM-D and the FM-S relations comprise 502 and 513, respectively (4060 face images). These images are for public figures gathered from the Internet. The face images are cropped using the position of eyes into 64 × 64 pixels resolution. For fair comparison, we restructured the database by separating the group of Father-Mother-Daughter into two groups Father-Daughter and Mother-Daughter kinship relations, and the group of Father-Mother-Son into two groups Father-Son and Mother-Son kinship relations. Therefore, we are restricted to the four kin relations as in the other databases.

Kinship-face-in-the-wild-database-(KinFaceW) [15] consists of two different sub databases: KinFaceW-I and KinFaceW-II. Both sub-databases are gathered through Internet research, including some public figures with their parents and/or children. In the KinFaceWI dataset, there are 156, 134, 116, and 127 pairs corresponding to the F-S, F-D, M-S, and M-D relations, respectively. For the KinFaceW-II dataset, each kin relation type contains 250 pairs. In total KinFaceW-I counts 1066 face images and 2000 face images for KinFaceW-II.

Fig. 1.4 (Left) Positive pairs (with kinship relation) and (right) negative pairs. From top to bottom the pairs are from Cornell, TSKinFace, KinFaceW-I and KinFaceW-II databases, respectively.



1.9 Conclusion

In this paper we provide a broad discussion of the concepts needed to understand kinship recognition through static facial images. We also focused on the difficulties and challenges that affect the efficiency of the facial kinship recognition model in practical applications from the perspective of pattern recognition and computer vision. In addition, we provided a simplified overview of a sample of the databases, technologies, and features that are used in this process.
The second present a simple approach that requires no training data by computing the distance between pairs of features with different functions and use the result as a score for deciding whether the pair is a kin or not. the distance which used is (the Cosine distance) The rest of the chapter, provided a brief discussion of the tools and techniques used. Functionality of feature selection algorithm is explained. Also, we explained the different fusion techniques and its related strategies. We presented the details of performance evaluation measurement throughout the thesis.

Finally, we illustrate that kinship score can be used as a soft biometric to boost the performance of any standard face verification algorithm. As a future research direction, in the future, it can develop more than ever, and this is a field that will face increasing interest over time by many researchers in all fields.

Chapter 02
Features Extraction

2.1Introduction

In this part, we explain the methods of extracting and categorizing features because they have an important role. Face image is an important guide to containing many useful human characteristics such as identity, features, age, expressions, etc., but the question that arises is about the types of features that help us identify relationships and how they are represented to determine Relationship. So, it will be an important challenge in estimating kinship. Therefore, it is necessary to focus on the feature extraction phase because of its clear impact on the performance of the recognition system.

Thus, we focus the research on the work ofCA-LBFL, kinship classification, and methods used to improve the accuracy of system performance.

Kinship verification is a binary classification problem where we enter a pair of faces and they are categorized into positive (the pairs are real for parents and children). or negative (not true for spouses and children). Then an optional stage called feature selection occurs. The goal of the algorithm is to select a feature that best defines a subset of the features used and that helps us deliver the smallest possible classification error.

2.2 Face Representation

Texture is an important characteristic of many kinds of images that range from multispectral remotely sensed data to microscopic images. Texture can play a key role in a wide variety of applications of computer vision and image analysis. As well, Image texture may provide information about the physical properties of objects, such as smoothness or roughness, or differences in surface reflectance, such as color [16]. Although texture is easy to identify, it is difficult to define. As a result, some very discriminative and computationally efficient local texture descriptors have been introduced. The performance gains offered by these new descriptors have led to significant progress in applying texture methods to a large variety of computer vision problems. Arguably, one of the best of these new local texture descriptors is the local binary pattern (LBP) operator.

2.3 Local Texture-based:

For expressing the non-occluded facial components and hence identifying the face, we used local binary patterns. A face picture is split into various areas in the LBP technique, from which LBP features are extracted and concatenated into an improved feature histogram that is utilized as a face descriptor. LBP achieves cutting-edge outcomes when it comes to representing and detecting facial patterns. The operator's discriminative power and computational simplicity, as well as its resistance to monotonic gray scale fluctuations induced by, contribute to LBP's effectiveness in face description. Variations in lighting, for example, The LBP technique is also resilient to face misalignment and position fluctuations because to the use of histograms as features.

2.3.1 Local binary pattern

Local binary pattern was first described by Ojala et al.[16] It is considered as an effective descriptor for texture classification. LBP operator's labels image pixels by Thresholding in the 3 × 3 neighborhood of each pixel with the center value and considering the result of this thresholding as a binary number. Mathematically, the LBP operator is defined as in Equation

$$\mathrm{LBP(N,R)} = \sum_{\mathrm{n=0}}^{\mathrm{N-1}} \mathrm{s(I_n - I_c)2^n} \qquad \textbf{(2.1)}$$

Where **N** is the number of pixels in the neighborhood, **R** is the radius, and the threshold functions$s(x) = 1\ if\ x \geq 0$, otherwise$s(x) = 0$. The $I_c$and $I_n$values are the gray levels of the center pixel and thex_{th} surrounding pixel, respectively.

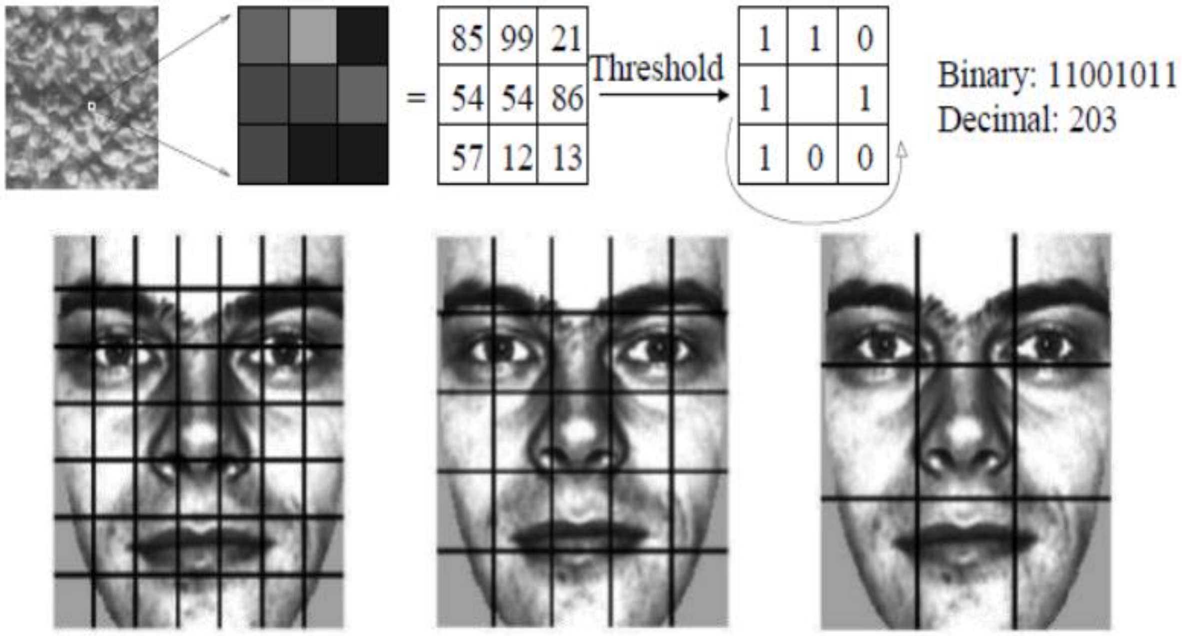


Figure.2.3. An example of the basic LBP operator.

2.4 Features extractions based on learned (No Hand-Crafted) features

2.4.1 Kinship with context information and metadata:

Recently, research attention has shifted toward contextual information involved in people centric photos. In kinship recognition, the hypothesis is that some similarities exist between two kin. For instance, kin can have similar mouth, eyebrows, eyes, forehead, and nose shape (facial cues). However, both the point and extent of similarities differ from one person to another, causing difficulty in establishing kinship using acial images only. Such information as location of photo, time when the photo is captured, clothing, position of a person in the photo, or any other text or link information provides contextual information that may help determine kin relation and improve accuracy.

2.4.2 Context-Aware Local Binary Feature Learning

In this section,we propose Active Context-Aware Binary Local Feature Learning (CA-LBFL) is a method that has been applied to learn contextual features from primitives directly and to eliminate dependence on handcrafted features. CA-LBFL exploits the contextual information of adjacent bits by restricting the number of transitions of different binary bits so that more powerful information can be exploited to represent a face.

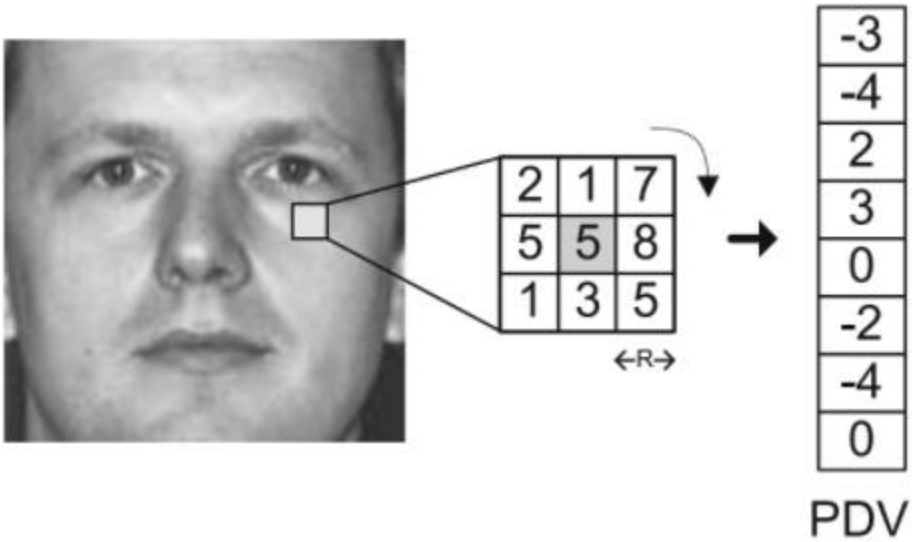


Fig.2.4. An illustration to show how to extract a pixel difference vector (PDV) from the original face image in our approach. Given any pixel in the image, we first compute the differences between the central pixel and its $(2R+1)\times(2R+1)$ neighboring pixels, where R is the parameter to set the neighborhood size. Then, these differences are aligned as a vector which becomes the PDV feature of the pixel. R is selected as 1 in this figure for easy illustration, so that the PDV is a 8-dimensional vector as there are eight neighboring pixels selected.

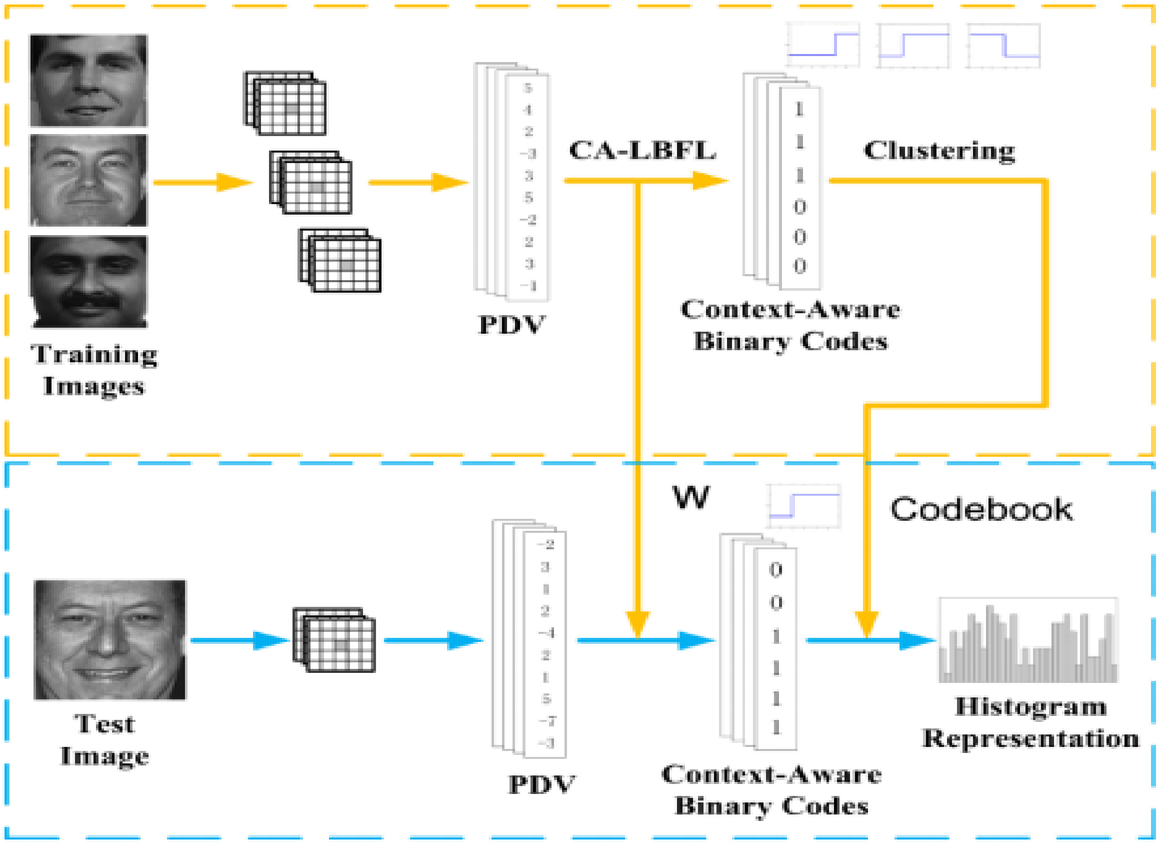


Figure.2.5. TheblockdiagramofCA-LBFL[17].

Projection Matrix W: We learn K hash functions to obtain context-aware binary codes, we map and quantize each $x_n$into a binary vector$b_n = [b_{1n}, \dots, b_{Kn}]^T \in 0, 1^{K*1}$. Let $w_k \in R^d$ be the projection vector for the k_{th} function, and the k_{th} binary code b_{kn} of x_n can be computed as:

$$\boldsymbol{b_{kn} = 0.5 * (sgn(w_k^T x_n) + 1)}\textbf{(2.2)}$$

where $sgn(v)$ equals to 1 if $v \geq 0$ and -1 otherwise.

Toobtainthebinarycodesforfeaturerepresentation, weformulatethefollowingOptimisation objective fonction:

$$min_{wk} J = J_1 + \lambda_1 J_2 + \lambda_2 J_3 + \lambda_3 J_4$$

$$= \sum_{n=1}^{N} || \sum_{K=1}^{K-1} || b_{kn} \quad - b_{(k+1)n} ||_2 - 1||^2$$

$$+\lambda_1 \sum_{n=1}^{N} \sum_{k=1}^{k} ||(\mathrm{b_{kn}} - 0.5) - w_K^T X_n||^2$$

$$+\lambda_2 || \sum_{\mathrm{k=1}}^{\mathrm{K}} \sum_{\mathrm{n=1}}^{\mathrm{N}} ||(\mathrm{b_{kn}} - 0.5)||^2$$

$$-\lambda_3 \sum_{n=1}^{N} \sum_{k=1}^{K} ||(\mathrm{b_{kn}} - \mu_k||^2 \quad \textbf{(2.3)}$$

Where N is the PDVs number which is obtained from the original images, the mean of the k_{th} bit of all N PDVs is μ_k. The three parameters, λ_1, λ_2 and λ_3 are used to equilibrate the weight of variant terms. In equation **2.3**, the physical meaning of $\sum_{K=1}^{K-1} ||\mathrm{b_{kn}} - b_{(K+1)n}||^2$ is the sum of bitwise 0/1 changes in each binary vector. The minimization of J_1 executes the contextual information and makes the codes more robust to the noises. J_2 aims to minimizes the loss of energy in the process of projection which reduce the loss of quantization between the binary codes and the original features. $J_3$is to evenly distribute the feature in the binary codes. J_4Project the vector as independent as possible by maximize the variance of the binary codes. We can mapped the projection matrix W and each sample x_n into a binary vector as follows:

$$0.5 * (sgn(w^T X_n) + 1) \quad \textbf{(2.4)}$$

Then, (2) can be re-written into the matrix form as:

$$min_w J = J_1 + \lambda_1 J_2 + \lambda_2 J_3 + \lambda_3 J_4$$

$$= tr(((AB)^T (AB) - I_N)^2)$$

$$+\lambda_1 ||(\mathrm{B} - 0.5) - \mathrm{W^T X}||_{\mathrm{F}}^2$$

$$= \lambda_2 ||(\mathrm{B} - 0.5) * 1^{\mathrm{N*1}}||_{\mathrm{F}}^2$$

$$-\lambda_3 ((B - U)^T (B - U)) \qquad \textbf{(2.5)}$$

Where$W = [w_1, w_2, \ldots . w_k] \varepsilon R^{d*k}$,the matrix of all binary codes B defined as

$B = 0.5(sgn(W^TX + 1)\epsilon 0, 1^{K*N}, U\epsilon RK * N$is the mean matrix repeating the row vector of the mean of all binary bits, IN is the identity matrix, and they minimize the difference between adjacent bits in binary codes using matrix Aϵ0, 1, $-1^{K-1} * K$as follows:

$$\begin{cases} 1, & i = j; \\ -1, & i = j = -1; \\ 0, & otherwise. \end{cases} \textbf{(2.6)}$$

The element of the matrix A is aij , and the indices are i and j. The differences between all the adjacent bits in learned binary codes are represented in matrix AB. and the diagonal of (AB) T (AB) is the sum of bitwise changes. Thus, J_1 can be rewritten as follows:

$$J_1(W) = tr(((AW^TX)^T(AW^TX) - I_N)^2)$$

$$= tr(X^TWA^TAW^TXX^TWA^TAW^TX)$$

$$-2 * tr(X^TWA^TAW^TX) + N \textbf{(2.7)}$$

Similarly, we rewrite J_3(W) and J_4(W) as:

$$J_3(W) = ||(\mathrm{W^TX} - 0.5) * 1^{\mathrm{N*1}}||_2^2$$

$$= tr(W^TX_1^{N*1}1^{1*N}X^TW)$$

$$-N * tr(1^{1*k}W^TX1_{N*1})$$

$$+0.25 * 1^{1*N} * 1 \textbf{(2.8)}$$

$$J_4(W) = tr(W^TXX^TW) - 2 * tr(W^TXM^TW)$$

$$+tr(W^TMM^TW) \textbf{(2.9)}$$

where $M \epsilon Rd \times N$ is the mean matrix which are repeated row vector of the mean of all PDVs. Therefore, they optimize W and B using the following iterative approach. Obtaining B with a fixed W: when W is fixed, equation 2.10 can be written as follows:

$$min_B J(B) = ||(\mathrm{B} - 0.5) - \mathrm{W}^{\mathrm{T}}\mathrm{X}||_{\mathrm{F}}^{2} \quad \textbf{(2.10)}$$

As B is a binary matrix, the solution can be directly obtained as:

$$B = 0.5 * (sng(W^T X) + 1) \quad \textbf{(2.11)}$$

Learning W with a fixed B: when B is fixed, the equation 2.12 can be written as follows:

$$min_w J(W) = tr(X^T W A^T A W^T X X^T W A^T A W^T X$$

$$-2 * (tr(X^T W A^T A W^T X) + (W^T Q W)$$

$$-2 * \lambda_1 tr((B - 0.5) * X^T W)$$

$$-\lambda_2 * N * tr(1^{1*K} W^T X_1^{N*1}) \quad \textbf{(2.12)}$$

subject to$W^T W = I$. Where

$$Q = \lambda_1 X X^T + \lambda_2 X_1^{N*1} 1^{1*N} X^T$$

$$-\lambda_3 (X X^T - 2 X M^T + M M^T \quad \textbf{(2.13)}$$

Unsupervised Clustering. The conventional K-means (unsupervised clustering) is used to learn the codebook to represent all binary codes as a histogram features.

2.5 Classification

If the extracted face features are discriminative enough, the classification can be simply performed with a linear classifier. Cosine similarity distance and thresholding have been used with mixed performance, while K-nearest neighbor classifier that measures the second-order distance of the features to find the nearest class seems to offer better performance Model-based classification utilizing a Metric Learning has shown superior performance when the amount of data allows the partition into meaningful splits of training and testing data [18].

We suggest a metric instructional workbook in this paper :

2.5.1 Metric Learning

In computer vision and machine learning, metric learning has received a lot of attention in last years. Number of metric learning algorithms has been proposed in the literature, they concerned to learn a distance function. The metric learning methods aim to seek an appropriate distance metric for classification tasks and have achieved a good performance in many facial image analysis applications. In this work, we present a simple method that requires no training data, we compute the distance between the pairs of features with different functions and use the result as a score for deciding whether the pair is a kin or not. distance are used in our case is :

Cosine similarity :

Set similarity is a difficult problem to solve using traditional rule based programming. The problem exacerbates when there is a large number of attributes in the dataset. Unsurprisingly, Math comes to rescue. Using the **Cosine fonction** &**K-Nearest Neighbor** algorithm, we can determine howsimilar ordifferent two sets of items are and use it to determine the classification.The Cosine function is used tocalculate the Similarity or the Distance of the observations in high dimensional space.If we want to compare how similar two items are, we represent each object or entity as a vector in Ndimensional space first, then we calculate the Cosine value of the angle between those two vectors.Fortunately, this cosine value can be easily computed as the dot product of the two vectors divided bythe product of their magnitudes [19].

Here’s a snippet of python code that computes the Cosine(θ) of two vectors:

```
import math
from collections import Counter


def cosine_similarity(v1, v2):
    terms = set(v1).union(v2)
    dotprod = sum(v1.get(k, 0) * v2.get(k, 0) for k in terms)
    magA = math.sqrt(sum(v1.get(k, 0)**2 for k in terms))
    magB = math.sqrt(sum(v2.get(k, 0)**2 for k in terms))
    return dotprod / (magA * magB)

#ref: quora
```

Cosine distance (cos) [20]: Cosine similarity is a measure of similarity betweentwo vectors and can be computed as:

$$dcos = \sum \frac{XiYi}{\sqrt{\sum_i x_i^2}\,\sqrt{\sum_i y_i^2}_{\,i}} \quad (2.14)$$

Where x and y are the two feature vectors of the pair of images being compared.

Figure 3.6 depicts the basic schema for facial kinship verification based on Metric Learning classifier.

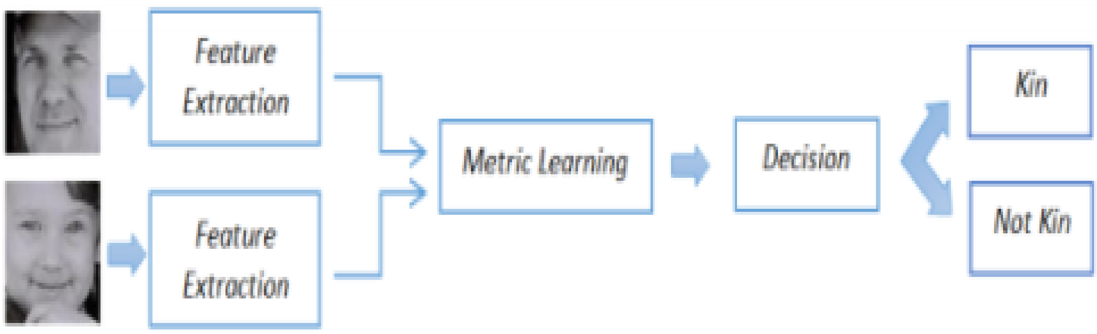


Figure 2.6: Kinship verification flowchart based on Metric classifier.

2.6 Feature selection

In machine learning, Feature Selection (FS) is a data preprocessing step that is applied after feature extraction step. Feature selection method aims to select the most relevant subset of extracted features to provide a useful classification with the smallest error and to discard non-relevant features. In this thesis, we used Fisher/Correlation feature selection using Wrapper for Spider toolbox [21], [22] and [23]. Spider Wrapper is a library of objects in Matlab. It is meant to handle large unsupervised, supervised or semi-supervised machine learning problems. The fundamental idea of choosing Fisher/Correlation (F/C) [24] score for kinship verification is to find a subset of characteristics, the distances between data points in same classes (positive pairs) are as small as possible, while the distances are as large as possible between data points in different classes (negative pairs).

Let $I = (xi , yi)|i = 1...N$ be the training data of pairs of parent and child images, where xi is the vector of the ith parent and y_i of the ith child, and **L** the class of this data. Each xi and y_i are ranked with Fisher/Correlation algorithm, next the size of the optimal (F/C) set is heuristically found.

The proposed feature selection method is presented in Algorithm 2.

Data: Input images, labels and the number of features to be selected.

Result: The selected features.

1.Transformation the pair features into a single feature vector using ***U.;***

2.Calculate ***S.;***

3. Output the features selected.;

In order to give a complete description of Feature Selection methodology, we detail each step of the previous algorithm: The input of the algorithm is: data $I = (xi , yi)|i = 1...N$, labels of data and the number of features to be selected.

First step. It based on normalized absolute difference **U** to transform the pair features into a single feature vector.

$$U = \sum_i \frac{|\mathrm{xi} - \mathrm{yi}\,|}{\sum_\mathrm{i}(\mathrm{xi} + \mathrm{yi})}$$

Where x are the parents images and y are the children images.

Second step. Select the most relevant descriptors of the input features based on Fisher score S.

$$S_i = \frac{\sum_{k=1}^{K} n_i(\mu_{ij} - \mu_i^2)}{\sum_{k=1}^{K} n_i n_j \rho_{ij}^2}$$

Where $\mu^j$is the mean, δ^jdenote the standard deviation of the whole data set and K= number of selected features.

Fisher score is one of the most widely used supervised feature selection methods. However, it selects each feature independently according to their scores under the Fisher criterion, which leads to a suboptimal subset of features.

We calculates the Fisher score for each feature by returning the fisher object initialized with parameter *(K: numSelec; the number of descriptors that are selected for each feature)*. In our experiments we change the K in order to identify the best performance for the algorithm.

Result. The output of the algorithm is features selected.

2.7 Performance evaluation

ReceiverOperatingCharacteristic**ROC** (receiver operating characteristiccurve)[27]is anaccepted method and widely used to show the effectivenessof a recognitionsystem.Curve**ROC** is graph showing the performance of aclassification model at all classificationthresholds.

This curve plots two parameters:

- ✓ True positive rate (ie. image classified correctly as positive pairs or negative pairs)

- ✓ False positive rate (ie. image classified incorrectly)

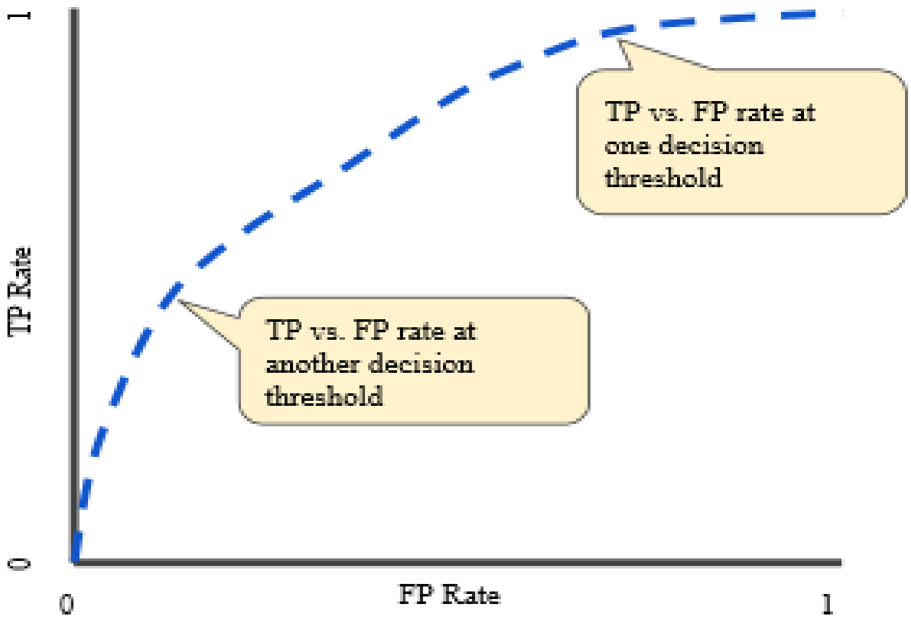


Figure.2.7.typical ROC curve.

Each PointontheROC**ROC**curverepresentsapositive/negativepaircorrespondingtoa particular decision threshold.Therefore,our evaluation performance is based on **ROC**curve and accuracy.More specifically [7]:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{P+N}} \quad \textbf{(2.15)}$$

TP: is the number of image that classified correctly as positive pairs.

TN: is the number of image that correctly classified as negative pairs.

P: is the number of all positive pairs.

N: is the number of all negative pairs.

2.8Brief Overview of Feature Normalization Techniques

Let and ix ̂ denote the original and normalized feature value respectively and further it is assumed that the specific feature contain 'N' values. Various normalization techniques investigated in this study are:

2.8.1 Feature Normalization (Z-score)

A very common technique to normalize the features to zero mean and unit variance is Z- score normalization [26]. It is a linear technique in which, initially, mean (x^{-}) and standard deviation (σ) of the specific feature values are computed using:

$$x^{-} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad \textbf{(2.16)}$$

and,

$$\delta^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - x^{-})^2 \textbf{(2.17)}$$

The normalization feature is then given by :

$$x_i^{\sim} = \frac{x_i - x^{-}}{\delta} \textbf{(2.18)}$$

Where $X^{\sim}$ represent the normalized vector andX: score vector.

3.9Cross Validation

Cross-validation, sometimes called rotation estimation or out-of-sample testing is any of various similar model validation techniques for assessing how the results of a statistical analysis will generalize to an independent data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice [22].

It is commonly used in applied machine learning to compare and select a model for a given predictive modeling problem because it is easy to understand, easy to implement, and results in skill estimates that generally have a lower bias than other methods.

2.9.1 K-fold Cross Validation

In k-fold cross-validation, the data is first partitioned into k equally (or nearly equally) sized segments or folds. Subsequently k iterations of training and validation are performed such that within each iteration a different fold of the data is held-out for validation while the remaining k-1 folds are used for learning. Data is commonly stratified prior to being split into k folds. Stratification is the process of rearranging the data as to ensure each fold is a good representative of the$whole$ [2].

In other words, the K-fold Cross-validation is a computer intensive technique, using all available examples as training and test examples [28]. **Figure 2.7** showed an example of5-cross validation.

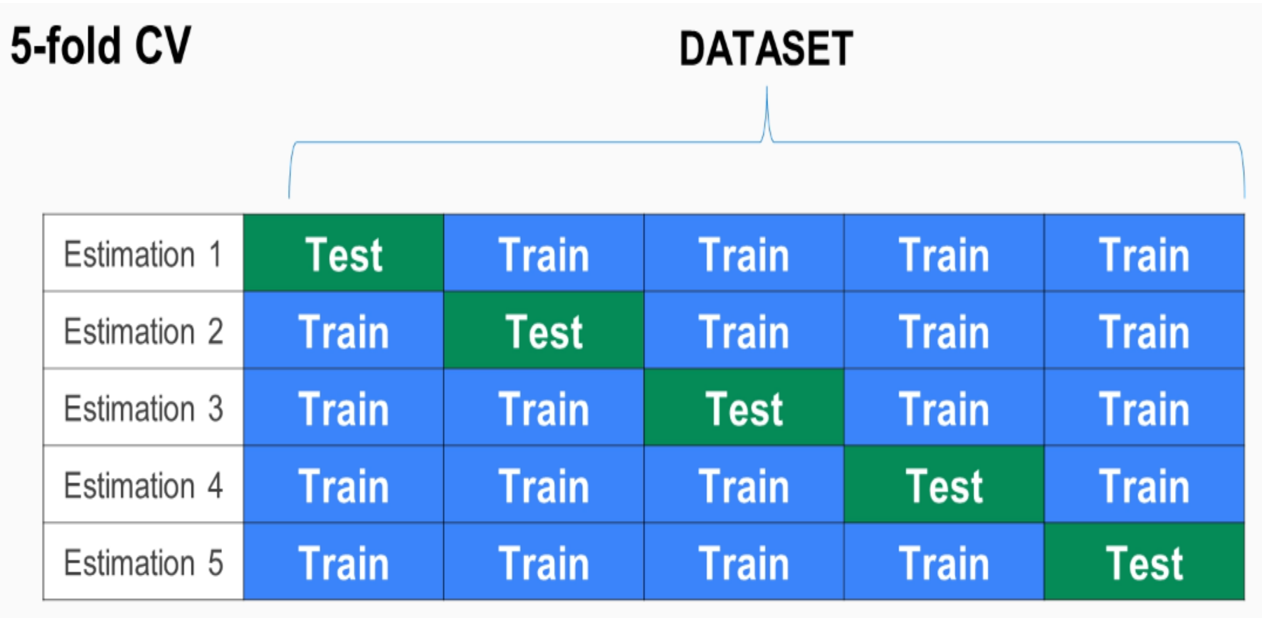


Figure 2.7: Example of 5-cross validation

Mathematically, the k-fold cross-validation operator is defined as following:

• Divide the data into K roughly equal parts.

• for each$k = 1,2,\ldots K$, fit the model with parameter λ to the other K-1 parts, giving $\beta^{-k}(\lambda)$ and compute its error in predicting the kth part:

$$E_k(\lambda) = \sum_{i \in k\text{th part}} (y_i - x_i \beta^{-k}(\lambda))^2 \quad \textbf{(2.19)}$$

• This gives cross validation error

$$CV(\lambda) = \frac{1}{k} \sum_{k=1}^{K} E_k(\lambda) \quad \textbf{(2.20)}$$

• Do this for many values of λ and chose the value of λ that makes CV (λ) smallest.

2.9 Conclusion

In this chapter, we gave an overview of automatic kinship verification from faces. We presented some notions and several definitions. The system design of facial kinship verification is described. Also, we discussed some exciting applications for the continuous research in this topic. We have also enumerated a number of practical challenges that restrain the facial kinship verification problems. Finally, summarized the existing databases.Moreover,different features extraction approaches are proposed to deal with kinship verification problem. We discussed the methods based on learned (No Hand-Crafted) features. The main advantage of the first method is constituted of power visual cues forfeiture description. They provide discriminating information about small appearance details in local neighborhoods. So, they are robust to local changes databases such as illumination, identity, geometric distortions and transformations, expression. The second method introducing the CA-LBFL . The CA-LBFLis applied to learn contextual features from raw pixels directly.

CHAPITRE 3
Results and Discussions

3.1 Introducation

We construct several studies in this chapter to use the notion of facial kinship verification that has been discussed throughout this thesis.

We offer the experimental findings of facial kinship verification tests that we have conducted. The CA-LBFL is investigated for feature extraction and cos-similarity is investigated for learning approaches. CA-LBFL is one of the learning methods. We do extensive tests on a variety of current kinship datasets. The data is evaluated and contrasted, and some intriguing conclusions are drawn.

3.2 Experimental 1

We'll start by looking into CA-LBFL feature extraction and similarity computing methods, and we'll tackle a variety of issues, including different ages, expressions, gender, skins, lighting variations, and even dramatic illumination. We'll also look at using the feature to extract complimentary data in order to increase kinship verification accuracy.

Power visual cues for feature representation are provided by local binary descriptors. They convey discriminatory information on minor physical characteristics in the community. As a result, they are resistant to changes in local databases like lighting, identification, and expression. It is not discriminating enough to assess the connection between two persons, unlike current local descriptors. This is mostly owing to the learning feature code and hand-crafted features, both of which need prior knowledge. In order to tackle the suggested challenge, we suggested an effective Context-Aware Local Binary Feature Learning (CA-LBFL) for kinship verification in this experiment. CA-LBFL is a technique that uses raw pixels to learn contextual features and eliminates the need for hand-crafted features. The suggested approach offers competitive outcomes when compared to existing state-of-the-art methods, according to experimental data. We conducted kinship verification tests on the difficult Kin Face W-II to assess the efficiency of suggested CA-LBFL approaches. Below is a quick overview of the databases that were utilized.

3.3. Experimental Evaluation

For the experiments, same number of negative pairs (no kin relation) as positive pairs (with a kin relation) is created by associating faces from persons which do not have a kinship relation. We apply the features selection technique to select the most relevant features. For each of the four kinship subsets (i.e. F-D, F-S, M-D and MS), we recommend taking the feature normalization technique to improve recognition rate. The result of normalization is that the features will be rescaled so that they all have properties of a standard normalization distribution. We perform 5-fold cross validation and compute the mean accuracy of the five folds. Finally, the cosine similarity of each test pair is computed. We report the mean verification accuracy of the four kinship subsets as the measure of system performance.

3.4. Parameter Adaptation

For the proposed CA-LBFL method, first we tested the mean area under ROC on KinFace in the Wild-II database with different parameters, and then applied these parameters for the rest of experiments. We fixed dictionary size as 600, the binary code length K as 40 and set R as 30. To achieve the best performance, we tested different values of λ1, λ2 and λ3. The results are shown in Table 3.1. The three parameters λ1, λ2 and λ3 were selected as 10^4 , $10^3$and 10^8 . We also tested different values of local region, finally, was fixed to 4 × 4, each face image was represented as a8000-dimensional feature vector after using CA-LBFL (8000 = 500 × 4 × 4). The results are shown in Table 3.2.

3. 5.Results and Analysis

To achieve the best performance, we tested different size of features to be selected on KinFaceW-II (F-S relationship) and then applied for the rest of relationships. The results are shown in Table 3..3. The final vector has size 891.

Table 3.1: Mean kinship verification accuracy in % on KinFaceW-II versus varying $\lambda 1$, λ2, and λ3.

Paramètres		**Accuracy**
$\boldsymbol{\lambda_1}$	$\boldsymbol{\lambda_2 \lambda_3}$	**F-S**
$10^4 10^2 10^9 85.0$		
$10^3 10^2 10^8 85.4$		
$10^3 10^4 10^7 85.6$		
$10^2 10^2\ 10^5 85.0$		
$\mathbf{10^4 10^3 10^8 88.4}$		
$10^4 10^4 10^8 87.0$		
$10^4 10^4 10^4 84.0$		
$10^2 10^3 10^8$	84.0	

Table 3.2: Mean kinship verification accuracy in % on KinFaceW-II versus varying local region.

Local	Region	Accuracy
2	2	82.8
4	4	88.2
6	6	88.4
7	7	84.0

Table 3.3.: Kinship verification accuracy in % of proposed method on KinFaceW-II databases (F-S) versus varying features number.

NumFeatures	FS relationships
797	87.0
701	86.8
883	88.0
403	85.4
533	85.6
331	86.2
891	**88.4**
901	87.8
902	88.0
884	88.2
864	88.0
863	87.4

Table 3.4: Kinship verification accuracy in % of proposed method onKinFace W databases.

Data Base	FS	FD	MS	MD	MEAN
KinFaceW-II	88.4	78.8	77.0	74.0	79.55

Table 3.5: Kinship verification accuracy in % of proposed method on KinFaceW-II databases under restricted setting.

Featureselection	FS	FD	MS	MD	MEAN
With	88.4	74.0	78.8	77.0	79.55
Without	69.2	65.0	67.0	64.8	66.5

Discussion: Our results show that the average accuracy of human performance on the task of kinship verification is 74.00 - 88.4 % on the Four relationships. The best verification accuracy is obtained for F-S with 88.0%.

Also, we tested our proposed method CA-LBFL with features selection against the CA-LBFL without features selection method. The performance of the CA-LBFL feature with features selection technique reports the best performance on the four relationships. Overall, the features selection enhanced the verification accuracy by a significant margin, F-S (improved by 19.2%), F-D (improved by 9.0%), M-S (improved by 11.8%), and M-D (improved by 13.05%).

Accordingly, fisher score feature selection is a useful technique to perform tasks without much effort and request expertise.

Table3.6: Comparison of proposed method against state of the art on Kin FaceW-II.

Method	Mean
GSML[25]	77.7
LML[17]	78.7
Deep features(CNN)[5]	79.39
IML[26]	76.10
OUR	79.55

Comparison with Baseline Methods: A comparison against other reported methods on Kin Face W-II is reported in Table. We compare the proposed method with various features under different strategies including Generalized Sparse Metric Learning (GSML) [25], Individual Metric Learning (IML) [26], Local Large-Margin Multi-Metric Learning(LML) [17] and Deep Convolution Neural Network [25]. These results show that our proposed approach outperforms the state-of-the-art methods.

Finally, while the literature suggests that exploiting the value of the contextual information of face images may also be able to improve kinship verification accuracy. We observe this effect in our data, but the accuracy of performance that has been obtained was not satisfactory. This indicates that this problem is extremely difficult and needs an effective solution due to the challenges that increase the proportion of errors and prevent the completion of the task.

Conclusion

In this chapter, we tackled the problem of automatic kinship verification from facial images considering four relationships: F-S, F-D, M-S and M-D. In this experiment, we relied on Context-Aware Local Binary Feature Learning (CA-LBFL) for facial kinship verification. The CA-LBFL is a method has applied to learn contextual features from raw pixels directly and to eliminate the dependence on hand-crafted features. Our study demonstrates the high efficiency of Context-Aware Local Binary Feature Learning in describing faces for kinship verification and shown its effectiveness compared with several state-of-the-art methods.

Conclusion

The purpose of the work presented in this thesis was the kinship verification from face images.

This thesis focus on kinship verification based feature extraction task. We presented an original investigation to detect the most significant characteristic features of human faces and it should help from the improved performance of kinship verification.

The Context-Aware Local Binary Feature Learning (CA-LBFL) is proposed to learn contextual features from raw pixels directly and to eliminate the dependence on hand-crafted features.

These methods have been validated on KinFaceIn the wild-II databases, and have been implemented under Matlab.

Also, feature normalization and feature selection are exploredto improve the kinship verification performance.

The aim of feature selection algorithm is to select the best subset of extracted features that gives the smallest classification error.In this thesis, we used Fisher/Correlation feature selection.

Fisher score is one of the most widely used supervised feature selection methods. However, it selects each feature independently according to their scores under the Fisher criterion, which leads to a suboptimal subset of features.

Finally, the cosine similarity of their features is used to compute their similarity.

Experimental results demonstrate that the proposed method achieves courageous results.

In the future, more work should be carried out for developing of advanced methods for kinship verification from videos. Also, development of novel methods for Kinship verification from gait, voice (and possibly also recording new databases if needed) and development of multimodal methods for Kinship verification from gait and voice.

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