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Multi-modal Biometric Person Identification
System Based on Finger Knuckle Print Features

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I dedicate this modest work

To the memory of my father, I constantly pray to the good god, that he may grant you his mercy and welcome you into his vast paradise n'challah.

To all my family for material and moral support

To all my friends where my sisters (Bouthaina, Hayat, Aicha, Houda, Soumia, Fatima, and also Imane, Fadhila and Aicha, who helped, supported and encouraged me.

To all my teachers during my years of studies with which I learned a lot.
I dedicate this modest work

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My sisters (Samra, Alla, Rinad) and my brothers (Faiçal, Mahdi, Houssin) especially for my cousins (Ilham and Ibtissam).

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Abstract
Biometrics is a branch of pattern recognition that is always attracting interest. Biometric systems make it possible to automatically identify people using physical or behavioral characteristics. Now more modality biometric used and give different results, the finger knuckle print (FKP) is one of the best between them because it is simple to use it and acceptable from the humans better yet, it gives a best performance. Feature extraction is the most important phase in biometric system because it gives accurate and the sole and comprehensive description from image. In this study, we discuss a review of system biometric based on hand biometric technology (FKP) using a simple deep learning method called Principal Component Analysis Network (PCANet). The study also takes the unimodal and multi-modal biometric systems results along with their methods of information fusion in score level.

key words: biometric, FKP, PCANet, unimodal, multi-modal, SVM
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<td>Cumulative Math Characteristic</td>
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<td>DNA</td>
<td>Deoxyribo Nucleic Acid</td>
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<td>DWT</td>
<td>Discrete Wavelet Transform</td>
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Chapter I

Introduction

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Chapter I. Introduction

Scientific research has taken a wide range in the present century the technology, where it covering all domains (medicine, trade, social, etc.), but this evolution has two different aspects, on the one hand facilitated the individuals lives, but on the other hand security is the most important field in the society, so the spread of violation and theft and the privatization breakthrough was the way to search for a primitive solution, which is to identify or verify individuals with a key or code PIN or Badge, but it was not very effective because of the ease of penetration.

Theft and forgetting are among the most important factors that the traditional system has experienced. It has lead up to the search for a system that can be developed using methods with greater precision and certainty. The human body offers the best solution for possessing unique properties known as biometrics. Biometrics introduced a new approach at the moment, as it was the ideal solution to many problems in the domain of security, because the characteristic of the human body cannot be stolen or forgotten, where the first use was the end of the 19th century [1, 2].

The advantage of these biometric characteristics is that they are universal, that is to say, present in all persons to be identified. On the other hand, they are measurable and unique: two people cannot possess exactly the same characteristic. They are also permanent, meaning that they do not vary or little over time [3]. However, the acceptability of using such a biometric system relates to the constraints associated with the acquisition and use of a biometric modality.

Unimodal biometric systems have increasingly been used in recent years as being based on a single modality, despite the advantages of these systems, their use suffers from several limitations, which can degrade the guarantee of the system, such as bad use of sensors, the inability to provide biometric characteristics and others [4]. These factors also lead to the emergence of multimodal system which combine information from multiple modalities [5].

I.1 Objective and motivation

The modalities in the biometric system have characteristics that distinguish each individual from another. The extraction stage is the process that you are interested by extract
the discriminant image characteristics of the modality of the person and its representation in the form of vectors. This operation interested in color, texture or form descriptors, it’s based by the different methods (LDA, DCT...), but the simple deep learning is new method used to texture feature.

The objective of our work is the study of a biometric identification system based on different samples of finger knuckle-print (FKP), our experience is based on deep learning PCANet feature extraction and Support Vector Machine (SVM) classification methods.

The use of multi samples of FKP for to increase the performance of biometric system and also increases the value of safe and trust to security systems based on biometric technologies and the use of PCANet is to view different representation of several levels to give together upper-level characteristics can be effective to represent the discriminating characteristics of FKP.

I.2 Thesis Outline

This brief is organized as follows:

Chapter II: includes an introduction to the biometric concept, operating modes of the biometric system, and finally some applications in which this system can be exploited.

Chapter III: is divided into two parts: the first part focuses on the use of the multi-biometric system, its various structures, in addition to explaining the fusion levels of its various operations (fusion rules). The second part is dedicated to explaining the image modeling and technique chosen namely deep learning PCANet.

Chapter IV: it presents the results and discussion of the identification system by the FKP modalities, in the following cases: unimodal system based on four fingers (lift index finger, left middle finger, right index finger and right middle finger), fusion of the two samples forming a multimodal system (lift fingers and right fingers).
Chapter II

INTRODUCTION TO BIOMETRICS

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Chapter II. INTRODUCTION TO BIOMETRICS

Technological development included all domains, but the hack and theft remained trader and more dangerous on the diverse systems, this problem, making the concept of security takes the context of the update.
We use classic systems (PIN, key, digital card ...), which has become an easy overtaking and infringed or loss of the other because of its disadvantages vulnerable to theft, falsification or lack ..., based on these results begin the search for more effective and guarantee.
At present, the biometric is the solution, although it is not the perfect solution but it offers several advantages over knowledge and possession based approaches in the way that there is no need to remember anything [6].
In this chapter, we present the basics of the biometric system based on defined and the different techniques used, also operating modes.

II.1 Definition of biometrics

The biometric is an operation can verify the identity of a person based on morphological, biological and behavioral characteristics in the human body (finger print, face, iris..., etc), or another way, it enables the identification or authentication of a person on the basis of recognizable and verifiable data of its own.
Biometric is derived from the Greek words, composed by two parts (“bio” means life and “metric” means to measure ), namely the biometric consists in automatically measurable personal features.

II.2 Biometric modalities

Biometric techniques used numerous, and different scientific references in classified, can be evaluated by two groups based on cooperation:

- **Intrusive techniques**: these techniques require physical contact with the individual to identify, such as fingerprints, retina, the iris or the hand geometry.
- **Non intrusive techniques**: these techniques do not require the cooperation of the individual. Their application can be done remotely using sensors that do not require direct contact with the user for example face [6, 7].

Instead of the broad categories (physiological, behavioral and biological attributes), for convenience the physiological modalities can be further sub-divided into different sub-categories according to their respective position in human body such as : hand region
attributes, facial region attributes, ocular region attributes, behavioral attributes, and medico-chemical attributes. The sub-division is illustrated in Fig. II.1 [8].

II.2.1 Hand region modalities

The hand is the body part at the end of your arm that includes your fingers and thumb, it composed by five parts contains rich texture information that provided the foundations for early recognition systems Fig. II.2.
Chapter II. INTRODUCTION TO BIOMETRICS

II.2.2 Facial region

Facial recognition is usually thought of as the primary way in which people recognize one to another [9]. This region encompasses the lower half of the head beginning below the ears, which include as shown in Fig. IV.8.

II.2.3 Ocular region

The ocular region includes the eyeball and associated structures. Most of the surface features of the ocular region protect the eye Fig. II.4.
II.2.4 Behavioral

Behavioral attributes establish identity based on the analysis of the way humans do the things. This type is based on the analysis of certain behaviors of a person as the traced his signature, his approach and his way of typing on a keyboard Fig. II.5.

II.2.5 Medico-chemical

This section contains the different elements of the classification, which can capture the identification by using chemical /medical equipment, which include body odor, DNA, Heart sound, Electro cardiogram.

For example DNA sampling is rather intrusive at present and requires a form of tissue, blood or other bodily sample. This method of capture still has to be refined. So far the DNA analysis has not been sufficiently automatic to rank the DNA analysis as a biometric technology. The analysis of human DNA is now possible within 10 minutes. As soon as the technology advances so that DNA can be matched automatically in real time, it may
II.2.6 Soft

Soft biometric traits like gender, age, height, weight, ethnicity, and eye color cannot provide reliable user recognition because they are not distinctive and permanent. However, such ancillary information can complement the identity information provided by the primary biometric traits (face, fingerprint, hand-geometry, iris... etc) [8].

II.3 Biometric Systems

Biometric systems are increasingly used in late years. Which acquires the biometric data of an individual, a set of characteristics extracted from this data and compares it to a set of data stored in advance in a database to finally perform an action or make a decision from the result of this comparison.

II.3.1 The structure of a biometric system

Biometric systems function through two tasks: enrollment, test phase.
✓ Enrollment phase: This is an apprenticeship phase. In this phase, which is used to create the reference database. Biometric characteristics of individuals is input by a biometric sensor, extract a set of features from these information, and finally stored in the database.
✓ Test phase: It can function a identification mode or verification mode
  ➥ Identification The user identification is a comparison "1 to N", where in the system recognizes an individual by pairing with a model of the database. The person may not be in the database. This mode consists of associating a identity to a person. In other terms, it answers questions such as "Who am I? ".
Also the mode identification divided into two modes operations (Open set and closed set)
  ✶ Closed set identification
The output of the biometric system consists of the identity of the person whose model (reference) has the highest degree of similarity with the biometric sample presented as input.
Open set identification
If the large similarity between the biometric sample and all models is lower (or higher) than a fixed safety threshold, the person is rejected, which implies that the user was not one of the persons enrolled by the biometric system.

Verification
It is the comparison 1-to-1 between the captured biometric data (model test), and the data stored in its own base (the apprenticeship models). In such a system, an individual who wishes to be identified claiming an identity, usually by means of a PIN (personal identification number), a user name, an identity card, etc. The system must answer the question "Am I really the person I am spirit to proclaim?" [9].

The three main modes in biometric systems have been displayed in Fig II.6.

Figure II.6: Diagram of a biometric system.
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The structure of a biometric system is typical, can be divided by five fundamental modules.

1. **The capture module**

Represent the biometric sensor, it captures a biometric data to extract a numerical representation for used in a phases the biometric system.

2. **Preprocessing module**

Or Quality Assessment, it allows for the reduction of the extracted numerical representation to optimize the quantity of data to be stored during the admission phase, or to facilitate the processing time during the verification and identification phases. This module can have a quality test to control the captured biometric data [10].

3. **Feature extraction module**

After taking biometric data from the capture module, it is extracted salient features or discriminatory information. Also so dispose of extra and unnecessary information, and form a new data

4. **The matching module**

Which compares the biometric data extracted by the characteristic extraction module to one or more previously stored models? this module, therefore, determines the degree of similarity (or of divergence) between two biometric vectors [11].

This module works either in verification mode (for a proclaimed identity), or in identification mode (for a searched identity).

5. **The decision module**

Verifies the affirmed identity by a user or determine the identity of a person based on the degree of similarity between the extracted characteristics and the model (s) stored (s) [11].

Database is unit that stores biometric information obtained from the System.

### II.4 Performance Evaluation of biometric systems

#### II.4.1 Performance measurements

Performance accuracy is how the system affected by external factors and the errors that can be committed, where they are measured in three basic criteria [12].
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a) False Accept Rate (FAR)

This is the percentage measure of invalid matches. It is a percentage the system recognizes unauthorized users as genuine users. For a robust biometric system, this error must be as low as possible.

\[
FAR(\%) = \frac{\text{number of accepted imposter (FA)}}{\text{total number of imposter access}} \quad (\text{II.1})
\]

b) False Reject Rate (FRR)

This is a percentage the system recognizes an authorized user as an impostor. It is the percentage measure of rejecting valid inputs. From user’s convenience point of view, this number must be low as much as possible.

\[
FRR(\%) = \frac{\text{number of rejected genuine (FR)}}{\text{total number of genuine access}} \quad (\text{II.2})
\]

As the false rejection (FR) corresponds to the case where the system rejected a legitimate customer. Another rate is widely used in the community; it is the rate of accepted clients

![Figure II.7: Distribution of curves impostors and clients.](image)

GAR or (Genuine Acceptance Rate). It is the rate of clients who are accepted by the
Chapter II. INTRODUCTION TO BIOMETRICS

system. This rate is important because it represents the suction of the biometric system.

\[ \text{GAR}(To) = 1 - \text{FRR} (To) \] (II.3)

Figure II.8: Distribution of curves Variation of GAR by FAR.

c) Equal Error Rate (EER)

Is a point defines the trade-off between the false rejects and the false acceptances, based on the two criteria (FAR and FRR), one can calculate the equal error rate, where FFR= FAR.

II.4.2 Graphic Performance Measurements

The biometric system operates by two main modes (verification or identification). From these modes, two types of curve can be classified to compare divers systems under the same conditions or to compare the operation of a system under different conditions [13].
a) Receiver Operating Characteristic (ROC)

Is a curve represents the variation of the FRR as a function of FAR. When the threshold varies; this graph graphically represents the performance of a verification or identification system. The equality error rate (EER) squares at the intersection of the ROC curve with the first bisector. It is frequently used to give an overview of the performance of a system. It is said to be performing if it has a reliable EER.

It is observed that the curve illustrates in the figure, the system gives maximum security values, because FRR takes values higher up to 100% (High-security), which means that the system can refuse clients too. On the other part, one notices that FAR reduces to 100%, any system to accept all clients with impostures often (Low-security). Zone compromise it represents the threshold where it is a perfect system.

![Figure II.9: ROC curves.](image)

b) Cumulative Match Characteristic (CMC)

In the closed set identification mode, there is the CMC ("Cumulative Match Characteristic") curve. This curve gives the percentage of people recognized according to a
variable called rank. This curve is associated by two criteria Rank of Perfect Rate (RPR) and Rank-One Recognition (ROR); ROR represents the most commonly used measure but it is not always sufficient. RPR which corresponds to ROR = 100% [6]. The fig. II.10 illustrates an example for CMC curve.

![CMC curve](image_url)

**Figure II.10:** CMC curve.

II.5 Application perspectives

Today, biometric systems are increasingly used in different domains, it responds to a very current requirement of shared security by individuals, enterprises and states alike [13]. Thereof, the applications of biometrics can be divided into three main groups:

- **Commercial applications:** such as computer network access, electronic data security, commerce, Internet access, credit card, physical access control, cell phone, medical registry management, distance learning, etc.
- **Government applications:** such as national identity card, driver’s permit, social security, border control, passport control, etc.
- **Legal applications:** such as body identification, criminal investigation, terrorist identification, etc.
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One can also add civilian applications that it more used by the biometric system, for example, using at the airport such as the procedure for checking passports and visas, and other applications as illustrated in the Fig.II.11.

![Figure II.11: Some biometrics applications.](image)

II.6 Conclusion

In this chapter we have introduced some basic concepts and definitions related to biometrics and its various regions which divides the modalities that finds them in the human body, the main modules of biometric systems and how to measure their performance. In the next chapter we will study multimodal biometrics systems.
Chapter III

MULTI-MODAL BIOMETRICS

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Chapter III. MULTI-MODAL BIOMETRICS

III.1 Introduction

From the above, we know that a biometric system was an alternative solution for person recognition problem, it defines itself as what we are, as opposed to what we have (e.g. badges, cards, and USB drive), or what we know (password and personal identification number (PIN) code).

Generally, this system based by two main phases (enrollment phase and test phase which include by identification or verification modes) starting from one modality, that’s why we said uni-modal biometric system, but the latter only guarantees 100% accuracy because of many factors (noisy data, intra-class variations, distinctiveness, non-universality, spoof attacks).

To reduce their factors, the access to the new strategy, this is multi-modal. The feature extraction is main module in the biometric system, the goal is to obtain a compressed representation, this operation based by the different methods such as PCANet.

In this chapter, we will present the objective of multimodal biometry and data fusion, and we present same notions about image modeling and picture features, than we study deep learning method (PCANet).

III.2 Definition of Multi-Modal biometrics

Multi-modal biometrics is the combination of multiple biometric modalities; it allows reducing certain limitations of systems based on a single modality while significantly improving their recognition performance by increasing the amount of discriminating information of each person and the use of additional information for a given person [14,15].

III.3 Categories multi biometrics

According to the nature of information sources, a multi-modal biometric system can be classified into categories [16–18].
III.3.1 Multi-sensor systems

Multi-sensor is based on the use of several sensors, be different use for one modality, this system extract accurate information, and to reduce the proportion of distorted data [19].

III.3.2 Multi-instance systems

This system takes several instances for a single modality for the variations that can occur within this modality. For example a facial recognition system can capture divers images of the face with changes of pose (Forehead profile, left and right profiles).
III.3.3 Multi-algorithm systems

These systems use different feature extraction and matching algorithms on a single modality acquired through a single sensor. Then, the individual results from each matcher are combined to obtain the final decision. Poor quality or distorted samples due to non-uniform illumination and improper sensor handling may affect overall performance of the system [20].

III.3.4 Multi-sample systems

Several different samples of the same modality are used, for instance, an individual’s left and right eye serves as an input to the system [21].
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III.3.5 Multi-biometric systems (Multi-character system)

These systems use multiple uncorrelated biometric signatures acquired through different imaging sensors. For example, iris and fingerprint of an individual is combined to establish the identity.

III.3.6 Hybrid systems

Hybrid systems concern other types of systems, they are composed of several scenarios from those presented above. Hybrid systems combine therefore have advantages information than previous systems.

III.3.7 Operations mode

Multi-modal systems can operate through two architectures, either serial or parallel.

a) Serial mode

According to Fig. III.7 the acquired multiple traits are processed one after another. The output of one trait serves as an input to the processing of next trait.
Chapter III. MULTI-MODAL BIOMETRICS

b) Parallel mode

This is the most used mode; the data is treated in same time and jointly for the acquisition of a large number of data. This mode makes an improvement in the system, as illustrated in the Fig. III.8 [22].

III.4 Fusion levels

In a multi-modal biometric system, the fusion can be done using the information available in any module of the system. The combination of several biometric systems can be done at four different levels: at sensor level, at the level of the extracted characteristics,
at the level of the scores coming from the comparison module or at the level of decisions of the decision module. These four levels of fusion can be classified into two sub-sets: Pre-classification fusion (before the comparison) and post-classification fusion (after the comparison) [23–25].

III.4.1 Sensor level

This level is the first level of fusion, based on the combination between the different information takes several sensors for arriving at a best quality. The figure II.10 show an example of sensor level by using DWT.

![Figure III.9: Multi-modal system based on fusion at the sensor.](image)

III.4.2 Feature level

In this fusion you can take information from several sensors, based on the extracted features of each piece is the merger in order to obtain a more precise features in the context of homogeneous data.
Chapter III. MULTI-MODAL BIOMETRICS

III.4.3 Decision level

Fusion at the decision level is often used for its simplicity. Indeed, each system provides a binary decision in the form YES or NO that can be represented by 0 and 1, and the fusion decision system consists in making a final decision according to the decisions of all the subsystems.

III.4.4 Score level

The merger score is level made after the comparison, process and it is more widely used for application to various subsystems to integrate dozens mechanism to create a new
partition for the adoption of a final decision [26, 27].

Figure III.12: Multi-modal system based on fusion at Scores.

III.4.5 Scores

The scores are the results generated by the recognition system during an identification mode the score indicates the person included in the client base that most closely resembles the person proclaiming. In this mode the result is a set of N scores where N is the number of people registered in the database and each score $S_i$ represents the likelihood between the test parameters and the model $\lambda_i$ saved in the database.

In order to ensure that these similarity vectors are coherent with each other, it is necessary to normalize them before considering a merge of the scores [28].
III.4.6 Scores normalization

Normalization is a valuable step for merging scores, as the distribution of scores from different systems is rarely compatible. One of the simplest normalization methods is normalization Min-max. It is used when the bounds of the score distribution are known. Using this technique, the scores are normalized between 0 and 1. From a set of scores $S_k, k = 1, 2, ..., n$, the normalized scores are obtained from the following way.

$$S'_k = \frac{S_k - \text{Min}}{\text{Max} - \text{Min}}$$ (III.1)

With min and max respectively the minimum and maximum scores; a normalization commonly used is the normalization by z-score in using the arithmetic mean $\mu$ and the standard deviation $\sigma$ of the data. It is therefore necessary to know or have available data to estimate this average and standard deviation. The standardized scores are obtained as follows [29].

$$S'_k = \frac{S_k - \mu}{\sigma}$$ (III.2)

III.5 Fusion rules

The methods of combining scores are very simple methods the goal is to obtain a final score $S$ from the $N$ scores available if for $i = 1$ to $N$ from $N$ systems. The most commonly used methods are the average, the product, the minimum, the Max-
Combining the scores by the mean consists of calculating $S$ such that:

$$ S = \frac{1}{N} \sum_{i=1}^{N} S_i \quad \text{(III.3)} $$

Combining the scores by the product consists of calculating $S$ such that

$$ S = \prod_{i=1}^{N} S_i \quad \text{(III.4)} $$

Combining the scores by the minimum consists of computing $S$ such that

$$ S = \min(S_i) \quad \text{(III.5)} $$

Combining the scores by the maximum consists of calculating $S$ such that

$$ S = \max(S_i) \quad \text{(III.6)} $$

Combining the scores by the median consists of calculating $S$ such that

$$ S = \text{med}(S_i) \quad \text{(III.7)} $$

All these methods are simple methods which require no adaptation. There are also some more advanced combining methods that require setting parameters as the weighted sum

$$ S = \sum_{i=1}^{N} W_i S_i \quad \text{(III.8)} $$

The weighted sum gives different weights to each of the subsystems depending on their individual performance or interest in the multi-modal system.

However, all these combining methods can only be used if all scores from the subsystems are homogeneous. For this, the methods of combining scores require a prior step of normalization of the scores [30].
III.6 Image Modeling

The image is a set of different information, so that each image has specific characteristics that create a difference between each image about other, this feature used in the recognition system, because it is special property and stable with time, also known for extracting characteristics among the most serious problems in the recognition.

There are factors that affect the image, they play the role of quality control and image clarity. The elements (luminance, chrominance “a” and chrominance ”b”) represent the basic layers of each image, so access to private information requires its selection according to fixed, non-changeable details.

Feature extraction is a stage interested in low level attributes such as (color, texture, and form) [31], but generally, It can be determined two types of image features can be extracted form image content representation (global features and local features) [32, 33].

1 Global features
Aim to describe an image as a whole and can be interpreted as a particular property of the image involving all pixels for example color and texture.

2 Local features
Aim to detect key points or interest regions in an image and describe them.
Specific features vary to (geometrical, singular points, lines, and texture) [34], according to that, different methods were identified for extraction divided into three categories:
- line-based technique (edge, Gabor filter with thresholding)
- appearance-based technique (PCA, LDA, ICA,GDA)
- texture-based technique (LBP, LPQ, HOG)

Figure III.14: Examples from the global features and local features.
III.7 Texture features

The methods used to identify discriminatory information differed from the results achieved in the permanent studies over the past years to the present, including the use of textures as a source of information. The researchers used this pattern over the past half a century, although it still offers exciting and effective results for attracting the attention of many of the algorithms and computational skills. Texture is actually a very nebulous concept, often attributed to human perception, as either the feel or the appearance of (woven) fabric. Everyone has their own interpretation as to the nature of texture; there is no mathematical definition for texture, it simply exists. And from this, the texture of an image is related to the spatial distribution of the intensity values in the image, and as such contains information regarding contrast, uniformity, rugosity, regularity, etc [35,36].

Figure III.15: Texture example.

III.8 PCANet Deep Learning

The difficulty of identifying special features, were allowed to update deep learning methods provide more accurate results based on texture analysis, among the latest of these techniques PCANet. PCANet is a simple deep learning baseline for image classification, based on three basic points (Principal Component Analysis (PCA), binary hashing, and histograms) [37,38].
Chapter III. MULTI-MODAL BIOMETRICS

PCA Filter bank
The filter banks are estimated by performing principal components (PCA) over filters. In this case, we represent the two stages where:

✓ The first stage
Depends on the presence of image input, using N principal components, we will get the output image N by taking the vectors.
We extract from each pixel of the image all of the K1×K2 that represents the patch size at all stages, where we collect them after converting them into special vectors for each image, than we take the mean of the entries for each vector, and we process the subtraction between this latter and the mean of each entry of the vector.
Through we evaluate PCA, using the vectors and retain the principal components, so that each principal component is a filter and may be connected to K1×K2 kernel which is convolved with the input image.

\[ I_l(x, y) = h_l(x, y) * I(x, y) \quad \text{where} \quad 1 \leq l \leq Ls_1 \quad \text{(III.9)} \]

✓ The second stage
This stage that follows the first stage directly by iterating the algorithm across all output images, where we take pictures resulting from the first stage [39,40].

\[ I_{l,m}(x, y) = h_m(x, y) * I_l(x, y), \quad \text{where} \quad 1 \leq m \leq Ls_2 \quad \text{and} \quad 1 \leq l \leq Ls_1 \quad \text{(III.10)} \]

Binary hashing
This stage is the level of transfer images obtained from the previous stage to binary format by using a Heaviside step function.
We binarize the output images resulting from the second stage; Followed by the conversion of each pixel features (x, y) has an associated N-dimensional to integers.

\[ I_{l,m}^B(i, j) = \begin{cases} 1 & \text{if } I_{l,m}(i, j) \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{(III.11)} \]

Histograms composition
The histogram of decimal values requires taking fragmented images and dividing them into NB blocks, where each block represents a special graph and it is either overlapping
or diverged according to determine the coefficient of overlap through the application.

\[ v_I = [v_{1}^{hist}, v_{2}^{hist}, ... v_{Ls1}^{hist}]^T \]  

(III.12)

Figure III.16: Proposed PCANet extracts features.

### III.9 SVM classifier

Support Vector Machine or SVM, it is a technique of discrimination and classification, based on the use of kernel functions, which allow an optimal separation of plan points into different categories.

It consists of separating two or more sets of points by a hyperplane. Depending on the case and the configuration of the points. The method uses a set of learning data, which makes it possible to establish a hyperplane separating at best the points.

#### III.9.1 Multiclass SVM

originally, SVM were designed primarily for 2-class problems, but several approaches to extend this algorithm to N-class cases have been proposed. The generalization in the multi-class case can be done in three different ways. The first two methods are based on
a multiplication of classifier bi-classes while the latter proposes a global resolution.

**One-against-all**: The most natural approach is to use this binary discrimination method and learn \( N \) decision functions for \( m = 1 \ldots N \) to discriminate between each class of all others (each class is opposite to all the others), so we need to ask \( N \) binary problems. The assignment of a new point \( x \) to a class \( C_i \) is done by the relation: \( i = \arg\max_{m = 1 \ldots N} F_m(x) \)

**One-against-one**: The second method is a one-to-one method. Instead of learning \( N \) decision functions, here each class is discriminated from another. Thus, \( N \times (N-1) / 2 \) decision functions are learned and each of them performs a vote for the assignment of a new point \( x \). The class of this point \( x \) then becomes the majority class after the vote.

**Overall method**: The latter method is an approach extending the notion of margin to multi-class cases. The problem involves \( N \) decision functions and it is very greedy in computation time and in memory space which means that it remains little used in real cases.

### III.10 conclusion

The multi-modal is a new trend, the combination of several biometric technologies or several recognition algorithms is presented, or various weighted systems are used to improve recognition performance, as explained in this chapter.

In fusion at the score level is applied by several methods after the normalization of scores. We have presented the simple methods of this level, an overview on an image modeling and deep learning method (PCANet) which based by descriptor of the texture.

In the next chapter, we will talk about the discussion and results of our experience with using the PCANet algorithm and Support Vector Machine (SVM) classification methods.
Chapter IV

Experimental Results and Discussion

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Chapter IV. Experimental Results and Discussion

IV.1 Introduction

Despite the different modalities used to study of the identification system, we chose Finger Knuckle Print (FKP), which represents the outer finger surface to extract the biometric features of the individual, because it’s permanent and stable, add to the satisfactory results achieved.

In this work, we studied the FKP system based on the PCANet and classification technique SVM to improve, through several sections. The first section we selected two sample from each hand (index finger and middle finger), and study each separately (left index finger, left middle finger, right index finger and right middle finger), in the second section, we examine the effectiveness of merging two samples LIF+LMF and RIF+RMF, than LF+RF (multi modal system), and then apply one of the results obtained with the different fusion rules (Sum, Mul, Min and Max). Finally, the third section includes the comment phase and determine the best results obtained.

IV.2 Proposed multimodal system

The proposed system is composed by two modalities, Fig. IV.1 illustrates the deviations of the levels experienced by the system, we have two sub-systems, which are integrated through the use one of the previously defined fusion levels (score level). The aim of this process is to ameliorate the results obtained in the study of each unimodal system separately.

The first system is the system of recognition by the Finger Knuckle Print (FKP), take two fingers from each hand (middle finger and index finger), the second system expresses the identification system by identifying the hand vein patter using special factors for each center.

Each subsystem based on two phases: the enrollment phase and the identification phase, the first phase, it interested by processing the image, then extract features on the form of vector at extraction module for we store in the database, the second phase, it based on the select template, and we compare it with all database. we merge the decisions resulting from each subsystem using the fusion.
We studied the proposed system based on two different databases of the PolyU Hong Kong Polytechnic University.

FKP database consists by 7920 images of 165 persons, divided into 125 men and 40 women, of whom 143 are between the ages of (20-30), and the rest between the ages of (30-50).

Each person is given 12 pictures for each image (LIF, RIF, RMF, LMF). This group is divided into two sessions, each session with 6 pictures [41].

For this work, we separating the data base to two main parts:

- **Learning images**: the first, fifth and ninth image of each person to serve learning phase.
- **Tests Images**: The remaining 9 images of each individual have helped us achieving different tests.
Chapter IV. Experimental Results and Discussion

IV.4 Experimental protocol

The aim of the system study is to achieve optimal results compared to previous studies using PCANet algorithm, in this work we followed the following steps:

- **First experimentation:** we studied the influence of the PCANet parameter in the identification rate of biometric system, and we choose the best parameter of PCANet feature extraction algorithm.

- **Second experimentation:** used the PCANet algorithm for extracting the features of finger knuckle print. These algorithms are among the best current texture descriptors. We conducted several experiments to see what is the best finger that give powerful results.

- **Third experimentation:** we have merged the different finger knuckle print samples for increased the performance of the identification system.

IV.5 Experimental results

IV.5.1 PCANet parameter adaptation

PCANet is a new approach that has been followed to evaluate the performance of the recognition system controlled by certain parameters very important the number of layer and number of filter in each layer and filter size and block wise histogram size and overlapping.

But it is very necessary to choose the best configuration of PCANet. In order to select the optimal parameter, we have made different tests.

Firstly, Table. IV.1 and Fig. IV.2, which illustrate the identification rate against the number of stage, we observe the use of two layers is the best result compared to the number of layers [1,3,4], because it gives the highest identification rate 91.51%.

The PCANet algorithm depends on the breakthrough texture, so we see one stage is not enough to extract information, on the other hand, the use of 3 and 4 stages causing deformation in the image, as a result the loss of principal information, when stage number equal 02, it presents a good information for a current texture descriptors.

As that a computational problem whenever the number of layers is greater than 4, because they require special equipment.
Chapter IV. Experimental Results and Discussion

Table IV.1: The variation of PCANet parameter of stage number.

<table>
<thead>
<tr>
<th>Stage Number</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification rate (%)</td>
<td>84.84</td>
<td>91.51</td>
<td>87.74</td>
<td>83.83</td>
</tr>
</tbody>
</table>

Figure IV.2: Identification rate against stage number.

To determine the filter number in the two layers, we fixed the stage number at 2 stages, we change the first layer filter between 1 and 12 filters. The table IV.2 shows the variation in first and second layer, and the Fig. IV.3 illustrates the identification rate against the number of first layer shows the change in first layer, we observe identification rate is very high in the filters [9-12], so that it gives the best result 97.17% when filter number equals 11, After that we have fixed a number in the first layer [filter number=11]. In the second layer, we note the identification rate of filters are very high from [5-10], where the filter 7 and 8 are achieved the best result 99.66%, but on the RPR side, the filter 8 gives best RPR.

Table IV.2: The layers variation of PCANet parameter.

<table>
<thead>
<tr>
<th>Filter number(L1)</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification rate(%)</td>
<td>94.2</td>
<td>95.55</td>
<td>95.89</td>
<td>96.16</td>
<td>96.36</td>
<td>96.76</td>
<td>96.96</td>
<td>97.17</td>
<td>96.96</td>
</tr>
<tr>
<td>Filter number(L2)</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
</tr>
<tr>
<td>Identification rate(%)</td>
<td>98.92</td>
<td>99.25</td>
<td>99.38</td>
<td>99.39</td>
<td>99.39</td>
<td>99.05</td>
<td>98.98</td>
<td>98.92</td>
<td>98.85</td>
</tr>
</tbody>
</table>
Chapter IV. Experimental Results and Discussion

Figure IV.3: PCANet parameters adaptation: a) the identification rate against the number of first layer. b) the identification rate against the number of second layer.

Through these qualifiers, we conclude that the filter number is essential in PCANet algorithm. Now, we change in filter size and block histogram size to determine their impact on this algorithm.

As a precondition, the filter size must be an odd number because it takes the center. We take the filter size values as follows [5, 7, 9, 11], the results are less than [5*5], we see that the best value at the filter size [5*5], because it gives high the identification rate estimated by 99.66% from the Table. IV.3 and the Fig. IV.4 PCANet parameters adaptation: a) the identification rate against the size of filter.

Another way, the block histogram size must be pair number. The Table. IV.4 and the Fig. IV.4 illustrates the different results obtained from changing the block-wise histogram size where [2*2] and [6*6] the value of the filter is increasing 99.46%, 99.59% respectively. the value [10*10] and [8*8] is stable, it provides the same results 99.66%, where the optimal block histogram size at [6*6] gives by 99.73%.

Table IV.3: The variation of PCANet parameter the filter size.

<table>
<thead>
<tr>
<th>Filter size</th>
<th>5</th>
<th>7</th>
<th>9</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification rate</td>
<td>99.66</td>
<td>99.39</td>
<td>98.72</td>
<td>97.17</td>
</tr>
</tbody>
</table>
Chapter IV. Experimental Results and Discussion

**Table IV.4**: Variation of PCANet parameter the block-wise histogram size.

<table>
<thead>
<tr>
<th>Block-Wise Histogram Size</th>
<th>2</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
<th>12</th>
</tr>
</thead>
</table>

**Figure IV.4**: PCANet parameters adaptation: a) the identification rate against the filter size. b) the identification rate against the block-wise histogram size.

We conclude that PCANet algorithm are affected by two basic factors (filter size and the block histogram size).

After making changes to various parameters, we try to improve performance with overlapping by taking ration [0%, 25%, 50%, 75%], it showed that the best results were obtained with 75%. Thus, the best identification rate is about 99.79%, but using the classification method SVM, we observe the best value is estimated by 99.86% were obtained with 50% ratio as illustrated the Table. IV.6 and the Fig. IV.5.

We use SVM methods because it’s technical classification (similarity), based on using kernel core functions that allow optimal separation of the points of the plan.

**Table IV.5**: The variation of PCANet parameter without SVM.

<table>
<thead>
<tr>
<th>Overlapping without SVM</th>
<th>0</th>
<th>0.25</th>
<th>0.5</th>
<th>0.75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification rate</td>
<td>99.05</td>
<td>99.25</td>
<td>99.73</td>
<td>99.79</td>
</tr>
</tbody>
</table>
Table IV.6: The variation of PCANet parameter with SVM.

<table>
<thead>
<tr>
<th>Overlapping with SVM</th>
<th>0</th>
<th>0.25</th>
<th>0.5</th>
<th>0.75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identification rate</td>
<td>99.66</td>
<td>99.46</td>
<td>99.86</td>
<td>99.79</td>
</tr>
</tbody>
</table>

Finally, after comparing the results we get better information PCANet algorithm:

The Number of Stages = 2
The number of filters = [11 8]
The filter size = [5 5]
The block size = [6 6]
The overlapping = 0.5%

IV.6 The application on a unimodal system

The purpose of the identification system is to evaluate the performance when we use information from each modality by establishing performance under different modalities (LIF, LMF, RIF, RMF). Through However, for all fingers, we use the best parameters of PCANet obtained in previously result. Generally, the identification system is divided into two basic stages (open set and closed set), so, we analyze the system according to these stages
Chapter IV. Experimental Results and Discussion

Table IV.7: The performance of the unimodal system with PCANet feature extraction.

<table>
<thead>
<tr>
<th>DB 165 person</th>
<th>Open Set</th>
<th></th>
<th></th>
<th></th>
<th>Closed Set</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EER</td>
<td>(T_0)</td>
<td>ROR</td>
<td>RPR</td>
<td>EER</td>
<td>(T_0)</td>
<td>ROR</td>
<td>RPR</td>
</tr>
<tr>
<td>LIF</td>
<td>0.08%</td>
<td>0.696</td>
<td>99.86%</td>
<td>58</td>
<td>0.008%</td>
<td>0.834</td>
<td>99.86%</td>
<td>05</td>
</tr>
<tr>
<td>LMF</td>
<td>0.008%</td>
<td>0.834</td>
<td>99.86%</td>
<td>05</td>
<td>0.0008%</td>
<td>0.984</td>
<td>99.93%</td>
<td>02</td>
</tr>
<tr>
<td>RIF</td>
<td>0.068%</td>
<td>0.708</td>
<td>99.86%</td>
<td>106</td>
<td>0.0008%</td>
<td>0.984</td>
<td>99.93%</td>
<td>02</td>
</tr>
<tr>
<td>RMF</td>
<td>0.068%</td>
<td>0.708</td>
<td>99.86%</td>
<td>106</td>
<td>0.0008%</td>
<td>0.984</td>
<td>99.93%</td>
<td>02</td>
</tr>
</tbody>
</table>

Figure IV.6: Unimodal system results a) ROC curves. b) CMC curves.

- **Open set**: we conducted several tests on (LIF, LMF, RIF, RMF) as shown in the figure and the table below, we observe that the results obtained take approximate values \(EER = [0.0008 \ 0.068]\) and \(T_0 = [0.696 \ 0.984]\), for each finger respectively (RIF, LMF, RMF, LIF) as illustrated the Table IV.7 and the Fig. IV.6 Unimodal system results a) ROC curves, the RIF gives the best values \(T_0 = 0.984\%\) and \(EER = 0.0008\%,\) the rest fingers gives best result when gives EER.

- **Closed set**: linked to two criteria ROR and RPR, based on the Fig. IV.6 and the Table IV.7, we note that (LIF, RMF, LMF) gives a same value for ROR estimated 99.86%, from RPR said take different values [58, 106, 05] respectively, and RIF gives 99.93% and RPR=02. Based on these experiment, the RIF gives best result.
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IV.7 The application on a multimodal system

The objective of this experiment was to study the performance of the systems when we merge information from certain fingers. In this case, the multimodal system operates with a single biometric modality (FKP) that proposes several samples. In our work, the merge at the score level is used because it is the most common approach used because of the best results and it is simple for merged scores generated by different subsystems. In order to achieve more effective results than the system unimodal, we use the fusion for merging the two samples of the same hand (LIF+LMF and RIF+RMF), then we combine the results obtained (LF and RF). and after that, we experiment with several fusion rules (Min, Max, Mul, Sum).

Fig. IV.7 and Table. IV.8 show the different results we note the decrease of the results after the fusion of the fingers, where we observe in the open set all the results of the fusion give the best result EER=0.00%, the same in the closed set, where we get the better results at the identification rate 100% of the first person.

Table IV.8: The performance of the multimodal system with PCANet feature extraction.

<table>
<thead>
<tr>
<th>DB 165 person</th>
<th>Open Set</th>
<th>Closed Set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EER</td>
<td>$T_\alpha$</td>
</tr>
<tr>
<td>LIF+LMF</td>
<td>0.00%</td>
<td>0.855</td>
</tr>
<tr>
<td>RIF+RMF</td>
<td>0.00%</td>
<td>0.801</td>
</tr>
<tr>
<td>LF+RF</td>
<td>0.00%</td>
<td>0.471</td>
</tr>
</tbody>
</table>

Figure IV.7: Multimodal system results a) ROC curves. b) CMC curves.
Chapter IV. Experimental Results and Discussion

Table IV.9: The performance of the multimodal system of different fusion rules with PCANet feature extraction.

<table>
<thead>
<tr>
<th>DB 165 person</th>
<th>Open Set</th>
<th>Closed Set</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EER</td>
<td>T_0</td>
<td>ROR</td>
<td>RPR</td>
</tr>
<tr>
<td>Sum</td>
<td>0.00%</td>
<td>0.855</td>
<td>100%</td>
<td>01</td>
</tr>
<tr>
<td>Mul</td>
<td>0.00%</td>
<td>0.657</td>
<td>100%</td>
<td>01</td>
</tr>
<tr>
<td>Min</td>
<td>0.00%</td>
<td>0.753</td>
<td>100%</td>
<td>01</td>
</tr>
<tr>
<td>Max</td>
<td>0.00%</td>
<td>0.995</td>
<td>99.79%</td>
<td>02</td>
</tr>
</tbody>
</table>

Figure IV.8: Multimodal system results of different fusion rules a) ROC curves b) CMC curves.

The Fig. IV.8 and Table. IV.9 shows the effect of different fusion rules on the performance of the multimodal system by choosing LF.

The open set showed the best result where EER=0.00% for all rules, and in the closed set gives each of the Sum, Mul and Min the ideal result ROR=100% and RPR=1, except Max rule gives a lower result estimated by ROR=99.79% and RPR=02.

Based on the above results, we conclude that the multimodal system gives better results to achieve EER=0.00% and an ROR=100% and an RPR compared than unimodal system result, so that their values as follows EER=0.0008% and an ROR=99.93% and an RPR=02.

IV.8 Conclusion

In this chapter, we studied the identification system FKP through the basic modules a pre-processing module which allows several techniques to be applied in order to extract the relevant parameters characterizing the FKP, a feature extraction module that allows
to represent the FKPs in the shape descriptors form of vectors, and a classification module that allows a class to the person we just identified, with decision making at the end either by accepting the person, or by rejecting it.

The experimental study of this system followed different stages to improve performance using feature extraction methods called PCANet. In the multimodal system, the merger of the samples and their study achieved better results than the unimodal system. Study each separate sample. Also, the fusion rules played a role in achieving results similar to those achieved by the multimodal system.
Conclusions and perspectives

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Chapter V. Conclusions and perspectives

V.1 Experimental Findings and Achievements

Today’s biometrics are a new passage of security system, it given their ever-increasing advantages and its access to various applications, the beginning was a unimodal system that relied on the use of single modality but the multimodal is a new strategy in the biometric system, where it was able to overcome the obstacles that the system unimodal suffers.

In this brief, we presented an overview on biometrics and some biometric techniques, a biometrics system, and a general overview of multimodal system with the fusion levels, than the applications of the different system (unimodal system and multimodal system) with the FKP modality, finally, we note all results obtain with discus. The goal of our work is to develop the recognition algorithm and improve the performance of identification through the Finger-Knuckle Print (FKP) modality using the extraction methods of deep learning PCANet advantage in order to better determine, for further improvement, we use Support Vector Machine (SVM) classification methods to make the system more appropriate, we have modified perfect settings for PCANet method, where the study of the unimodal system achieved positive results related by lift index finger, lift middle finger, right index finger, and right middle finger.

The RIF gives best result in unimodal system, but the application of the combination of samples LIF+LMF and RIF+RMF also used to improve reached it gives the best process EER=0.00% and ROR=100%.

Also, the study at the level of changing the fusion rules, it achieved impressive results for the Sum, Mul, Min.

V.2 Perspectives for Future Work

As the perspective, we will use another modality like (finger vein, palm print . . . ), or we use a new deep learning methods namely DCTNet, this method is very similar structure to PCANet, but the difference between them in the filter type.

Also, in the multimodal system technique, we apply another combination between (finger knuckle print + finger vein).
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