



HAL
open science

Biometric recognition based on hand shape and palmprint modalities

Nesrine Charfi

► **To cite this version:**

Nesrine Charfi. Biometric recognition based on hand shape and palmprint modalities. Image Processing [eess.IV]. Ecole nationale supérieure Mines-Télécom Atlantique, 2017. English. NNT : 2017IMTA0003 . tel-01781354

HAL Id: tel-01781354

<https://theses.hal.science/tel-01781354>

Submitted on 30 Apr 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

**UNIVERSITE
BRETAGNE
LOIRE**

THÈSE / IMT Atlantique

sous le sceau de l'Université Bretagne Loire
pour obtenir le grade de

DOCTEUR DE IMT Atlantique

*Mention : Sciences et Technologies de l'Information
et de la Communication*

École Doctorale Sicma

Présentée par

Nesrine Charfi

Préparée dans le département Image et Traitement
de l'Information

**Reconnaissance biométrique
basée sur les modalités
de la forme de la main et
de l'empreinte palmaire**

**Biometric recognition based
on hand shape and
palmprint modalities**

Thèse soutenue le 23 janvier 2017

devant le jury composé de :

Ali Khenchaf

Professeur, ENSTA Bretagne / président

Jean-Paul Haton

Professeur, Université Henri Poincaré Nancy 1 / rapporteur

Kamel Hamrouni

Professeur, Ecole National d'Ingénieurs de Tunis (Tunisie) / rapporteur

Najoua Ben Amara

Professeure, Ecole Nationale d'Ingénieurs de Sousse (Tunisie) / examinatrice

Adel Alimi

Professeur, Ecole National d'Ingénieurs de Sfax (Tunisie) / examinateur

Basel Solaiman

Professeur, IMT Atlantique / directeur de thèse

Hanène Trichili

Maître de Conférences, Université de Sfax (Tunisie) / invitée

Remerciements

J'exprime ma profonde gratitude à **Monsieur Basel Solaiman**, Professeur à l'Ecole Télécom Bretagne campus Brest et mon directeur de thèse pour m'avoir accueilli au sein de son équipe de recherche. Son expérience et son aide scientifique m'ont été essentielles. Sa disponibilité ainsi que l'attention qu'il a portée à ce travail ont été un atout précieux dans le suivi et l'avancement de mes travaux de thèse.

Mes vifs remerciements vont à **Monsieur Adel M. Alimi**, Professeur à l'Ecole Nationale d'Ingénieurs de Sfax et co-directeur de thèse, pour m'avoir accueilli au sein du laboratoire groupe de recherche sur les machines intelligentes REGIM-Lab et avoir assuré jusqu'au bout le suivi de mes recherches. Qu'il trouve ici l'expression de mes sincères considérations et reconnaissances, pour ses conseils et ses critiques utiles, qu'il m'a prodigués tout au long de la réalisation de ce travail.

Je tiens à exprimer ma profonde reconnaissance à **Madame Hanene Trichili**, Maître assistante à l'Université de Sfax et mon encadreur pour m'avoir proposée un sujet porteur et passionnant. Qu'elle trouve ici l'expression de mon respect le plus profond pour ses encouragements, son aide et ses conseils prodigieux au cours de la réalisation de ce travail.

J'adresse mes sincères remerciements à **Monsieur Jean-Paul Haton**, Professeur à l'Université Henri Poincaré Nancy et à **Monsieur Kamel Hamrouni**, Professeur à l'Université de Tunis El Manar, pour l'honneur qu'ils me font d'avoir accepté l'évaluation de cette thèse.

Je tiens aussi à exprimer ma gratitude à **Monsieur Ali Khenchaf**, Professeur à ENSTA de Bretagne qui me fait l'honneur de présider le jury de ma thèse.

Je remercie également **Madame Najoua Ben Amara**, Professeur à l'Université de Sousse d'avoir accepté de faire partie de mon jury et examiner ce travail.

Je remercie également mes collègues, du laboratoire REGIM-Lab et du laboratoire ITI de Télécom-Bretagne, que j'ai eu le plaisir de côtoyer et pour l'ambiance, leur aide et conseils qu'ils m'ont apportés durant la réalisation de ce travail.

Mes sincères remerciements s'adressent tout particulièrement à mes chers parents. Mon père **Moncef** qui m'a soutenu dans tous les moments, les bons comme les difficiles. Ses encouragements continus ont été, pour moi, fondamentaux pour pouvoir continuer et réussir au cours de mon cursus. Ma mère **Dorra** qui a pris le temps de m'écouter et entendre mes histoires de biométrie. Ses sacrifices, sa douceur et sa tendresse ont toujours mérité mon grand amour et respect. Merci pour la confiance que vous m'avez toujours accordée.

Une dédicace spéciale pour ma chère sœur **Leyla** qui a toujours su m'encourager dans les moments difficiles de stress. Sa patience, son amour et sa tendresse ont toujours mérité mon plus profond respect. Je remercie également mon cher frère **Mohamed** pour ses encouragements et son aide continue même à distance. Je leurs souhaite le succès dans leur vie aussi bien professionnelle que familiale.

Je tiens enfin à exprimer ma gratitude pour ma famille et mes amis et à tous ceux qui ont contribué à l'accomplissement de ma thèse, par leur aide morale ou matérielle.

Résumé

La biométrie est une alternative qui se base sur l'identification des personnes à partir de leurs caractéristiques physiques (empreinte digitale, forme de la main, empreinte palmaire) et/ou comportementales (voix, signature dynamique). La biométrie tend à réaliser deux buts importants dans notre vie courante. Le premier but est de réaliser la sécurité en éliminant le doute sur l'identité d'une personne et le second but est de faciliter l'identification des individus. En effet, cette méthode d'identification est de plus en plus préférée par rapport aux méthodes traditionnelles impliquant les mots de passe et les badges. Les travaux de recherche de cette thèse s'inscrivent dans le cadre de la reconnaissance de personnes à l'aide de la biométrie de la main. L'objectif principal est de concevoir un système biométrique multimodal basé sur la fusion de la forme de la main et de l'empreinte palmaire. La première partie de cette thèse propose un nouveau système uni-modal de vérification de la forme de la main. En effet, ce système est basé d'une part, sur la détection du meilleur ensemble des points-clés localisés sur le contour de la main pour adopter la description SIFT (Scale Invariant Feature Transform). D'autre part, un raffinement de correspondance, basé région et apparence de la main est proposé, afin de raffiner autant que possible les points-clés faussement matchés.

Tandis que la deuxième partie consiste à proposer un nouveau système d'identification palmaire. En effet, la méthode de représentation parcimonieuse est adoptée afin de décrire le trait biométrique de l'empreinte palmaire. Elle est basée sur l'extraction de descripteurs SIFT de chacun des points-clés détectés.

Notre troisième partie concerne la proposition de différentes méthodes de fusion multi-types de la multi modalité, comprenant la fusion multi-représentation, la

fusion multi-biométrique et la fusion multi-instance. En effet, la fusion multi-représentation est basée sur la combinaison de descripteurs SIFT et les caractéristiques géométriques de la main au niveau des scores, pour la vérification de la forme de la main. La fusion multi-biométrique est basée sur la combinaison des deux modalités biométriques à savoir la forme de la main et l’empreinte palmaire, au niveau des caractéristiques et de la décision. Par contre, la fusion multi-instance est basée sur la combinaison des empreintes palmaires droite et gauche, au niveau du rang. Ces différentes méthodes de fusion ont prouvé leur efficacité en obtenant de meilleurs taux de reconnaissance, qui sont compétitifs par rapport à d’autres approches multimodales de la biométrie de la main.

Mots-clés: Biométrie, forme de la main, empreinte palmaire, multimodalité, fusion.

Abstract

Biometry is a technology which is based on the personal identification using their physical features (fingerprint, hand geometry, palmprint) and/or behavioral features (voice, dynamic signature). Biometry aims to achieve two important goals in our current life. The first one is to ensure security by eliminating doubt regarding the identity of a person and the second one is to facilitate the identification of individuals. Indeed, this method of identification is increasingly preferred over traditional methods including passwords and badges. The research works of this thesis talk about the personal recognition using hand biometrics. The main objective is to design a multimodal biometric system based on the fusion of hand shape and palmprint modalities.

Our first part is to propose a new unimodal biometric system for hand shape verification. In fact, this system is based firstly, on the detection of the best set of keypoints located on the contour of the hand for further SIFT (Scale Invariant Feature Transform) description. On the other hand, a matching refinement based hand region and appearance is proposed in order to refine as much as possible false matched keypoints.

Our second part consists in the proposition of a new palmprint identification system. In fact, the sparse representation method is adopted in order to describe the palmprint biometric trait. It is based on the extraction on SIFT descriptors for each detected keypoint.

Our third part concerns the proposition of multi-type fusion methods for multimodality, including the multi-representation fusion, the multi-biometric fusion and the multi-instance fusion. Indeed, the multi-representation fusion method is based on the combination of SIFT descriptors and geometrical features of the

hand, at score level. The multi-biometric fusion method is based on the fusion of hand shape and palmprint modalities, at feature and decision levels. On the other hand, the multi-instance fusion method is based on the combination of left and right palmprints, at rank level.

These different methods of fusion have proven their effectiveness by achieving encouraging recognition rates that are competitive to other popular multimodal hand biometric approaches.

Keywords: Biometry, hand shape, palmprint, multimodality, fusion.

Contents

Contents	vii
List of Figures	x
List of Tables	xii
1 General introduction	1
1.1 Context of the research and motivation	1
1.2 Problem statement and objectives	4
1.3 Contributions	5
1.4 Outline	8
I LITERATURE REVIEW	9
2 General context of biometry	10
2.1 Introduction	12
2.2 Identity verification of a biometric system	12
2.2.1 Identity verification	12
2.2.2 Biometry	13
2.2.3 Biometric modalities	14
2.2.4 Properties of biometric modalities	15
2.2.5 Advantages and disadvantages of each biometric modality	16
2.2.6 Verification and identification	16
2.2.7 Structure of a biometric system	18
2.2.8 Evaluation of a biometric system	19
2.3 Multimodality	21
2.3.1 Limitations of unimodal biometric systems	21
2.3.2 Different multi-types	23
2.3.3 Architectures of multimodal systems	24
2.3.4 Fusion levels	26
2.4 Why hand modality ?	31
2.4.1 Presentation of some biometric modalities of the hand	31
2.4.2 Principal challenges of hand modality	34
2.5 Conclusion	36

3	Hand shape and palmprint modalities: a survey	37
3.1	Introduction	39
3.2	Hand Shape Modality	39
3.2.1	Hand image acquisition	39
3.2.2	Hand detection	43
3.2.3	Hand feature extraction	48
3.2.4	Matching module	50
3.2.5	Decision-making module	50
3.2.6	Discussion and overview of different hand shape approaches	51
3.3	Palmprint modality	54
3.3.1	Characteristics of palmprint modality	54
3.3.2	Palmprint image acquisition	55
3.3.3	Palmprint Region Of Interest (ROI) extraction	57
3.3.4	Palmprint feature extraction	59
3.3.5	Overview of different palmprint approaches	63
3.4	Multimodal hand shape and palmprint biometrics	66
3.4.1	Challenges of using multimodality	66
3.4.2	Design of multimodal biometric systems	66
3.4.3	Overview and discussion of hand shape and palmprint fusion approaches	67
3.5	Conclusion	69
II	CONTRIBUTIONS	72
4	Verification approach based hand shape modality	73
4.1	Introduction	75
4.2	Methods and techniques	76
4.2.1	Scale Invariant Feature Transform (SIFT)	76
4.2.2	Gabor filters	78
4.3	The proposed Sift Matching Refinement based Hand Shape Verification (SMRHSV)	79
4.3.1	Preprocessing module	79
4.3.2	The matching refinement	82
4.4	Experimental evaluation	85
4.4.1	Experimental corpus	86
4.4.2	Verification results	86
4.4.3	Execution time performance	88
4.5	Discussion and comparison	88
4.6	Conclusion	89
5	Identification approach based palmprint modality	90
5.1	Introduction	91
5.2	Methods and techniques	91
5.2.1	Sparse representation (SR) concept	91

5.2.2	Support Vector Machines (SVM)	95
5.3	Proposed identification approach based palmprint modality	96
5.3.1	Palmprint ROI extraction	96
5.3.2	Feature extraction	97
5.3.3	Palmprint identification	99
5.4	Experimental evaluation	100
5.4.1	Proposed prototype	100
5.4.2	Experimental results	101
5.4.3	Execution time performance	105
5.5	Conclusion	105
6	Proposed hand multi-types fusion for multimodality	106
6.1	Introduction	108
6.2	Multi-representation hand shape verification method	109
6.2.1	Feature extraction module	110
6.2.2	Matching score	110
6.2.3	Information fusion method	111
6.2.4	Experiments and results	111
6.3	Multi-biometric hand recognition method	115
6.3.1	Hand shape and palmprint fusion for persons verification	115
6.3.2	Hand shape and palmprint fusion for persons identification	121
6.4	Multi-instance palmprint identification method	131
6.4.1	Fusion at rank level using probability distribution	131
6.4.2	Experimental evaluation	135
6.5	Summary and conclusion	137
7	Conclusions and future work	141
	Bibliography	145
	List of publications	159

List of Figures

1.1	Relationships between the different objectives of the design of a biometric system [Kong 2009].	5
2.1	Different biometric modalities	14
2.2	Structure of biometric systems	19
2.3	FAR and FRR diagram	20
2.4	ROC curve	20
2.5	Example of CMC curves for different face poses used to identify a person based on his face [Buddharaju 2007]	21
2.6	Different types of multimodal biometric systems [Jain 2007].	24
2.7	Architecture of fusion in parallel	25
2.8	Architecture of fusion in series	25
2.9	Different fusion levels of biometric systems	26
2.10	Flowchart of general fusion at feature level.	27
2.11	Concatenation of attribute vectors.	28
2.12	Hand shape.	32
2.13	Hand geometry features.	33
2.14	Palmprint region.	33
2.15	Five finger surfaces.	34
2.16	Some examples of environmental challenges.	35
2.17	Some examples of acquisition challenges.	35
2.18	Some examples of occlusion challenges.	36
3.1	General hand recognition process.	40
3.2	Examples of hand acquisition devices [Morales 2008, Kumar 2006a].	41
3.3	Evolution of active contour $\Gamma(\tau)$ toward the object of interest [Lamard 2010].	44
3.4	Characteristics of palmprint modality	54
3.5	Examples of palmprint acquisition devices [Zhang 2010].	57
3.6	ROI extraction of Tiwari et al. [Tiwari 2013]: (a) hand image, (b) ROI detection on hand contour, (c) extracted region square of palmprint ROI.	58
3.7	ROI location of Hammami et al. [Hammami 2014]: (a) determination of the palm width L, (b) ROI detection with $[OO_1]=1/10L$ and $[E_1E_2]=2/3L$	59
4.1	The position of the proposed hand shape verification method vs. different approaches existing in the literature.	75

4.2	Keypoint description in different orientations (8 directions)	77
4.3	The proposed hand shape verification method.	80
4.4	(a) Original hand image (b) Binary hand image (c) Wrist removal using reference point and centroid.	81
4.5	(a) Binary image (b) Radial distance function (c) Localization of five fingertips and four finger valleys.	81
4.6	Localized keypoints:(a) using original SIFT detector, (b)using proposed 150 points, (c) using proposed 300 points.	82
4.7	False matches between two keypoints (red matches) localized in different regions.	83
4.8	(a) Detected hand landmark points (b) Hand divided into six regions (the palm and the five fingers).	84
4.9	Hand boundary patch definition.	85
4.10	Examples of IITD hand database.	86
4.11	ROC curve performances of the proposed approach Vs. original SIFT algorithm.	87
5.1	The position of the proposed palmprint identification method vs. approach types.	92
5.2	Illustration of sparse representation principle	92
5.3	Separating hyperplane of the SVM.	96
5.4	Palmprint segmentation:(a) Grayscale original image; (b) Orientation according to vertical axis; (c) Detection of midpoints M_1 and M_2 ; (d) Detection of palmprint ROI; (e) Palmprint image extraction.	97
5.5	Some examples REST hand database.	101
6.1	Overview of the different multi-types treated in our work.	108
6.2	Overview of the different fusion schemes treated in our work.	108
6.3	Flowchart of the proposed multi-representation method.	109
6.4	ROC curve of FAR and FRR relative to matching score fusion results.	112
6.5	Comparative performance of hand geometry and hand shape features using score level fusion.	112
6.6	The proposed SMRPPV system	115
6.7	Fusion scheme.	118
6.8	Fingers segmentation.	118
6.9	Block diagram of the proposed identification system.	122
6.10	Architecture of the proposed fusion scheme.	123
6.11	Correct Identification Rate (CIR) in terms of different numbers of subjects of IITD hand database.	128
6.12	Flowchart of the proposed palmprint identification method.	132
6.13	Example of triangular probability distribution.	134
6.14	CMC curves of the proposed fusion method over REST hand database.	136

List of Tables

2.1	Comparisons of biometric modalities according to seven properties: Universality (U), Distinctiveness (D), Stability (S), Collectability (Co), Acceptance (A), Circumvention (Ci), Performance (P). ● ● ●:high degree, ● ●:medium degree and ●:low degree.	17
3.1	Some hand databases existing in the literature.	42
3.2	Comparison of some hand shape/geometry biometric systems proposed in the literature.	53
3.3	Some palmprint databases existing in the literature.	57
3.4	Comparison of some palmprint biometric systems proposed in the literature.	64
3.5	Comparison of some fusion approaches of hand shape and palmprint modalities.	70
4.1	Performance verification rates (%)	87
4.2	Comparison of performances results of our hand shape verification approach vs. other popular approaches	87
4.3	Execution time	88
5.1	Comparison of the CIRs of the proposed approach and other popular approaches over IITD hand DB	102
5.2	Correct identification rates over REST hand database	102
5.3	Correct identification rates over CASIA palmprint database	103
5.4	Comparison of the CIRs between the proposed approach and other popular palmprint approaches over CASIA palmprint DB	104
5.5	Execution time	105
6.1	Performance verification rates (%).	113
6.2	Performance comparison with different approaches in term of equal error rate (EER).	114
6.3	Comparison of verification results of palmprint systems.	119
6.4	Performance verification rates with different fusion methods of hand shape and palmprint modalities.	120
6.5	Performance verification rates.	120
6.6	Performance comparison with different approaches in term of equal error rate (EER) using IITD hand database.	121

6.7	Correct identification rates, CIR (%) of the different keypoints detection for various population size of IITD hand database	126
6.8	Comparison of hand shape CIR (%) between different detected keypoints using Bosphorus hand DB	126
6.9	Comparison of hand shape biometric system performance vs. an existing system in the literature using IITD hand DB	127
6.10	CIR (%) of the proposed system using IITD hand DB	128
6.11	CIR (%) of the proposed system using Bosphorus hand DB	128
6.12	Comparison of performances between the proposed approach and other existing approaches fusing hand shape and palmprint modalities	130
6.13	Execution time	131
6.14	Correct identification rates over REST hand database	136
6.15	Correct identification rates over CASIA palmprint database	137
6.16	Comparison of performances between different multi-instance palmprint methods over toucheless databases	138
6.17	Comparison between the different proposed multi-types	140

Chapter 1

General introduction

Contents

1.1	Context of the research and motivation	1
1.2	Problem statement and objectives	4
1.3	Contributions	5
1.4	Outline	8

1.1 Context of the research and motivation

The security and safety of individuals, properties and information need to be guaranteed, and present actually one of the major concerns of our societies, especially after the great spread of terrorism around the world. In fact, people willing to cross boundaries must prove their identities using their passports. People willing to cross buildings or academic institution must validate their access cards. People desiring access to banking services must log in using a login and a password. Nevertheless, these traditional methods show great weaknesses for identity verification. Indeed, the identity of a person is directly related to that they possess (such as passport, access card, etc.) or/and that they know (password, PIN codes, etc.). Nonetheless, PIN codes and passwords may be forgotten or compromised and access cards may be falsified or duplicated which lead to identity spoofing. In

this respect, experts are looking for a technology which resolves these problems by giving more convenience to persons and ensuring a highly secured access, by relating the identity of a person to that they are and not to that they possess or know. Biometry is the most suitable technology for identity verification and/or person identification by employing their physiological features including biological, morphological and behavioral characteristics. This technology makes identity data theft more difficult and thus increases user confidence as the physical presence is necessary during identification.

Historically speaking, biometry appeared in order to succeed the anthropometric recognition. The oldest one was fingerprint analysis, used by the police for persons identification. In the 19th century, a french criminologist invented a scientific method named "forensic anthropology" to identify criminals based on their physiological measures. In fact, this use has never been abandoned and fingerprints are still used for criminal identification. Nowadays, the increasing power of computers may contribute to individual recognition thanks to complex computer algorithms used in devices. Hence, biometry is actually a developing science which aims to identify individuals through technological systems, using their biological characteristics. It is no longer limited to fingerprints and criminal identification. Several other modalities are used today namely iris, face, hand shape, gait etc. for access control applications. The use of this technique is widespread around the world and takes an important place in our daily life. In the coming years, biometry will probably be one of the most employed techniques, firstly to identify or authenticate individuals and secondly to control access for public spaces such as banking, airports, hospitals, museums, railway and bus stations.

Previously, different unimodal biometric systems based on unique biometric modality have been developed. While unimodal biometric techniques promise to be very efficient, however, we may not guarantee an excellent recognition rate. Indeed, they present three main limitations, which are as follows: limitation in terms of performances, limitation in terms of universality of use and limitation in terms of fraud detection. The first limitation concerns performances of recognition due

to possible variation of biometric modalities during their acquisition or also naturally. For example, in the case of face biometrics, the face varies according to expressions, lighting conditions and positions of capture. Indeed, it is not possible to find two identical images corresponding to the same person. This variability of biometric features may badly effect identity recognition performances. The second limitation is ascribed to the non-universality of certain biometric modalities. This means that a subject may not possess some modalities to be authenticated or may not have sufficiently informative modality allowing their identity verification. For instance, a mute person cannot use a voice biometric system or a disabled person cannot use a gait biometric system. Therefore, some biometric systems are inaccessible for these subjects, and they may be excluded if no other alternative is offered. Regarding the third limitation, it relates to fraud detection. In fact, fraud or identity theft is a problem that occurs quite often. Biometrics reduced this problem (since it is easier to falsify a password or an identity paper than to reproduce a hand or a face), but did not eradicate it. It is possible, for example, to steal fingerprints (as they leave traces) or to reproduce them (using silicon).

All these limitations may be solved or removed by using several biometric modalities called multimodal biometric systems. In this context, the works presented in this thesis are located. Various multimodal approaches are proposed here, using different multi-types fusion that are multi-representation, multi-biometrics and multi-instance fusions for both identification and verification modes. These approaches are based essentially on hand shape and palmprint modalities. In fact, our motivation to use these modalities is due to the popularity of hand biometric trait. Compared to other biometric modalities, the hand presents the following advantages:

- The hand acquisition devices are simple and inexpensive.
- The hand trait is more acceptable by the public compared to other modalities.
- The hand information may be extracted using low resolution images.

- Additional biometric modalities including palmprints and fingers may be embedded in a developed hand shape biometric system.

1.2 Problem statement and objectives

The design of each biometric system should take into account five important and related factors which are cost, accuracy, user acceptance and environment constraints, security and computation speed (figure 1.1). In fact, decreasing accuracy may increase speed, decreasing user acceptance may improve accuracy and increasing cost may ameliorate security.

To increase user acceptance, two biometric modalities are acquired simultaneously from a single acquisition of the hand trait. Nevertheless, hand biometrics present some problematics which may deal with respecting the mentioned objectives. Indeed, previous hand biometric systems were based on the direct contact of the hand trait with the system device of capture, which may decrease user acceptance. For this reason, recent works have been focusing on contact-less and contact-free acquisition systems making it more comfortable and hygienic by eliminating the contact obligation. However, the liberty of presenting one's hand provides several variabilities such as scaling changes, hand orientation changes, positions variability, illumination changes etc. Moreover, the cost of the acquisition device may be expensive for the capture of high resolution images, especially for palmprint biometric trait. Thus, several works adopt low resolution images of the hand during acquisition module. Research in this area is certainly interesting via the multiplicity and diversity of these problems. In fact, hand biometric modality has received much attention from research laboratories as well as industrial ones.

According to these problems and in order to ensure the design of our hand biometric system success, our objectives are focused on the proposition of a solution which increases the accuracy and the speed of the person recognition process, decreases the cost of the biometric system and increases the user acceptance. Hence, our

solution is based on a contactless multimodal hand biometric system fusing various parts of the hand modality, and satisfying the different objectives mentioned above. Thus, two unimodal methods for hand shape verification and palmprint identification have been, firstly, proposed. On the other hand, several multi-types approaches have been developed including multi-representation, multi-biometric and multi-instance, using the proposed unimodal methods to ensure higher security. It should be noted that the proposed solution is not intended to real-time applications.

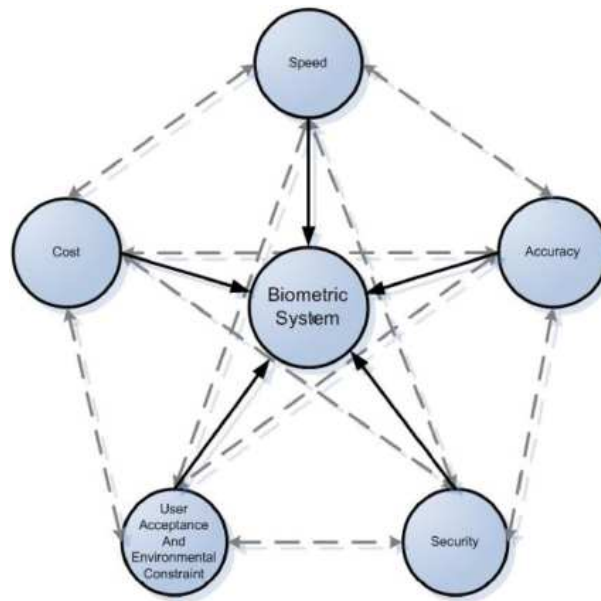


FIGURE 1.1: Relationships between the different objectives of the design of a biometric system [Kong 2009].

1.3 Contributions

In order to achieve the objectives detailed in the previous section, some contributions are suggested for verification and identification approaches based on hand biometric modalities. The contributions of this thesis are summarized as follows:

- **Localization of hand landmarks and SIFT description:** [Charfi 2015b]

Our first contribution consists in the detection of landmark points localized on the contour of the hand for further Scale Invariant Feature Transform

(SIFT) description. In fact, the hand shape modality is represented by the contour of the hand. Thus, unlike other biometric systems that employ SIFT detector to localize keypoints on the biometric trait image (such as iris or fingerprint), our aim is to localize independently keypoints localized on the contour of the hand rather than keypoints detected using SIFT detector method. A specific number of detected keypoints demonstrates that this method may achieve better performances. In fact, to our knowledge, there is no similar research work that has been proposed in the literature using SIFT descriptors in the context of hand shape biometric recognition. This method showed that SIFT features are robust and efficient for hand shape recognition purpose [Charfi 2014].

- **Matching refinement process based on shape and appearance of the hand:** [Charfi 2016c]

Standard algorithm of SIFT description presents a principal problem. Indeed, the orientation histogram-based SIFT features are insufficient for the discrimination of each keypoint because of the ignorance of the orientation positions by histograms. To overcome this problem, a new approach based SIFT contactless hand shape verification is proposed.

In fact, our contribution consists in refining matched SIFT keypoints using two matching refinement levels. The first one is based on region refinement in which matched keypoints belonging to different hand regions are considered as false matched and they have to be removed. The second one is based on texture (or appearance) refinement method called Boundary Hand Descriptor (BHD) in which a patch centered in each point is extracted and Gabor filters are employed for texture extraction. Experimental results indicate that the proposed method is efficient and high verification rates may be achieved.

- **Fusion of hand shape and palmprint biometric modalities by integrating fingers ROI for persons verification:** [Charfi 2016c]

This contribution concerns the integration of the finger surface features into the fusion scheme of hand shape and palmprint modalities. Indeed, in our fusion scheme, hand shape and palmprint modalities are fused at decision level. In the case of similar decisions, the final decision is provided. Otherwise, the five finger surfaces are segmented and their features are extracted in order to confirm the identity of the claimed person. This method allows the reduction of computational complexity while increasing performance rates.

- **Hand shape descriptor based on sparse representation and fusion scheme of hand shape and palmprint modalities for persons identification:** [[Charfi 2016a](#)]

Unlike other biometric methods that extract SIFT descriptors and proceed generally to SIFT matching so as to match testing and training images, our identification method consists in representing sparsely SIFT patches centered on keypoints localized on the contour of the hand. Therefore, SIFT descriptors are transformed to SIFT sparse representation as a descriptor of both hand shape and palmprint modalities, in order to feed the classification task. In addition, overall multimodal biometric systems adopt either a single fusion level for recognition or several fusion levels to compare their results and find the most efficient level. However, in our work, we propose a hybrid multimodal fusion using two fusion levels : the feature fusion level and the decision fusion level. In this hybrid multimodal fusion, we employ a cascade scheme, so as to generate the final decision about the identity of the person. To our knowledge, there are no works that include these proposals in their biometric systems. Experiments show better performances compared to popular multimodal methods existing in literature.

- **Multi-instance fusion for palmprint identification :** [[Charfi 2016b](#)]

This contribution concerns the palmprint identification area. It consists of the fusion of left and right palmprints at rank level. In fact, after the classification step, the similarity distances (scores) are computed for each image sample. These scores are considered as the belonging degree of each image

to all classes (persons). However, ambiguity still exists between palmprints of some classes which may result in a mis-classification. Hence, our purpose is to transform these scores into probability measures. Afterwards, the ambiguity difference is computed based on the ratio of probability measures of the second most relevant class and the first most relevant class. The final identity decision is provided according to the ambiguity ratio measured from the two palmprint instances (left and right). If the ambiguity ratio measure of the left palmprint is higher than the measure of the right one, the person's identity of the right palmprint is considered. Otherwise, the person's identity of the left palmprint is considered.

1.4 Outline

The thesis is structured as follows: Chapter 2 reports the general context of biometry. Chapter 3 presents a survey of hand shape and palmprint modalities in which the state of the art of these two modalities is detailed. Chapter 4 describes the proposed persons verification based on hand shape modality. However, chapter 5 focuses on the proposed persons identification approach based on palmprint modality. Chapter 6 depicts the proposed hand multi-types fusion for hand shape and palmprint modalities. Finally, the last chapter concludes the thesis and discusses its most important results and contributions. Future works and perspectives are also put forward.

Part I

LITERATURE REVIEW

Chapter 2

General context of biometry

Contents

2.1	Introduction	12
2.2	Identity verification of a biometric system	12
2.2.1	Identity verification	12
2.2.2	Biometry	13
2.2.3	Biometric modalities	14
2.2.4	Properties of biometric modalities	15
2.2.5	Advantages and disadvantages of each biometric modality	16
2.2.6	Verification and identification	16
2.2.7	Structure of a biometric system	18
2.2.8	Evaluation of a biometric system	19
2.3	Multimodality	21
2.3.1	Limitations of unimodal biometric systems	21
2.3.2	Different multi-types	23
2.3.3	Architectures of multimodal systems	24
2.3.4	Fusion levels	26
2.3.4.1	Fusion before matching	26
2.3.4.2	Fusion after matching	28
2.4	Why hand modality ?	31
2.4.1	Presentation of some biometric modalities of the hand	31
2.4.1.1	The hand Shape/geometry	31
2.4.1.2	The palmprint	33
2.4.1.3	The fingers	34

2.4.2	Principal challenges of hand modality	34
2.5	Conclusion	36

2.1 Introduction

Biometry is a growing technology which has become increasingly used in our daily life. It aims to establish the identity of a person as reliable as possible using their biological features in order to guarantee the safety of people in public places. In this chapter, we introduce firstly, the identity of a biometric system, structure, advantages and disadvantages of the different biometric modalities. Subsequently, we define the multimodality notion. Eventually, we display the advantages as well as the challenges of hand modality.

2.2 Identity verification of a biometric system

Identity is a philosophical notion related to the personality of each individual. Indeed, person's identity is defined as the distinctive characteristic which makes a person unique among other individuals. A person is identified since their birth with a name and some personal data such as date and place of birth, family, social security number, ... which are increasingly verified during their life. Each person has to claim their identity in several opportunities (bank account, access local, across frontiers, etc.). In the past, persons identification was a manual task, but today it has become numeric and automatic task. Biometry is the most efficient identification way since it relies increasingly on the identity of a person mainly in terms of distinctive features (physical or behavioral).

2.2.1 Identity verification

Fraud has not ceased to increase in our society, which feels the need to control every day. Security applications require user authentication. Until now, this authentication has been done using identification ways relying on a thing that we know or that we possess. Passwords or other codes correspond to things that we know, whereas badges, cards or identity documents correspond to things that we

possess. These two identification ways may be combined, as in the example of the credit card which is based on the possession of the card and the knowledge of the secret code to use it. However, these identification ways present a bundle of disadvantages such as falsification, robbery, loss, etc.

Regarding identity documents, other problems may be tackled at deliverance. In fact, an identity document may not only be lost or falsified but also exposed to more serious frauds which consist in realizing original documents for false identity. In this case, one person can have several identities which may cause a lack of security especially if this person is a criminal. Indeed, it is difficult to know if a person who is presented to obtain an identity document, has not already been possessing documents with another identity. However, with biometric data, it would be possible to verify if this person does not possess other identities by comparing his biometric data to the set in database. An efficient way to resolve these different issues presented by traditional authentication ways is biometry. Indeed, biometry is the recognition of individuals by who they are rather than what they know or what they possess.

2.2.2 Biometry

Biometry is the verification of individual identity based on his biological characteristics which are classified into two categories. The first one is physical characteristics which are most commonly used and rely on physical traits of individuals such as iris, fingerprint, palmprint, face, etc., and the second kind is behavioral characteristics which are less used and rely on individual actions or behaviors such as walking, voice, dynamic signature, etc. These physical and behavioral characteristics that allow persons identification are called biometric modalities.

Biometry tends to be used, nowadays, in biometric systems aiming at making automatic recognition. In fact, the idea to characterize individuals based on their physical traits is not new. It has already been used and developed in the 19th century with the launching of the traditional technology of biometry which is the

anthropometry. Therefore, police have used, since the 19th century, fingerprints as a way of criminals identification. However, this recognition was manual and was executed by experts. Today, the development and growth of computer techniques allow the automation of these processes.

2.2.3 Biometric modalities

There are different kinds of biometric modalities which can be classified into two categories: morphological biometric and behavioral biometric. Morphological biometric consists of using a part of the human body such as fingerprint or iris. As for behavioral biometric, it uses a person's behavior trait such as signature or walking. There are also morpho-behavior biometrics namely voice, which relies at the same time on the morphology of vocal cords and the behavior since voice may change easily depending on the emotional state of the person. Figure 2.1 demonstrates some examples of different biometric modalities.

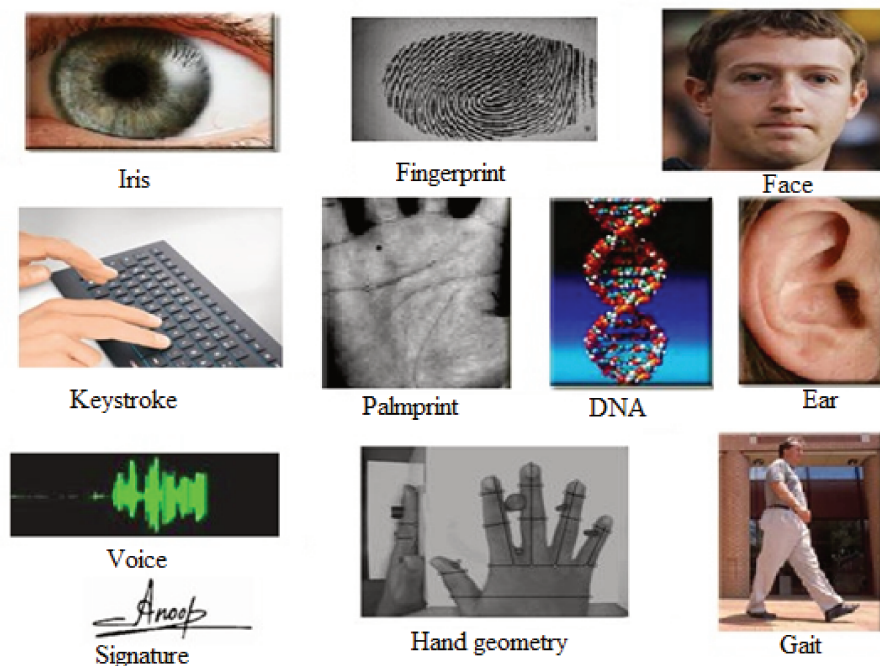


FIGURE 2.1: Different biometric modalities

2.2.4 Properties of biometric modalities

Biometric authentication presents several advantages compared to traditional identification ways like passwords or cards because it establishes a strong link between an individual and their identity. Principal properties of a biometric modality are the following:

- **Universality:** The whole population should possess this modality (physical or behavioral characteristic).
- **Distinctiveness:** Two different individuals must have different biometric representations.
- **Stability:** To ensure individual authentication success, biometric modality should be relatively stable over time and it also has to be stable regardless conditions of acquisition (external conditions, emotional conditions of the person, etc.).
- **Collectability:** The biometric modality must be acquired.
- **Acceptance:** The acceptance and the facility of usage are related to the acquisition constraints of a biometric modality.
- **Circumvention:** The biometric modality must not be easily falsified.
- **Performance:** Biometric recognition should be accurate, fast and robust with regards to operational and environmental changes.

All modalities do not possess all these properties, or may possess them with different degrees. Hence, there is no ideal or perfect modality. The trade-off between presence and absence of some of these properties is required according to each system needs, regarding the choice of biometric modality.

2.2.5 Advantages and disadvantages of each biometric modality

A comparison between different biometric modalities according to the seven properties mentioned previously (universality, distinctiveness, stability, collectability, acceptance, Circumvention, performance) is presented in table 2.1. The quality degree accorded to each modality is classified into three classes: high, medium and low referred to the following notations ●●●, ●● and ●, respectively.

This table originating from [Jain 2004] indicates that behavioral biometric modalities (keystroke, odor or signature) present low recognition performances unlike intrusive data such as methods based on DNA or retina. However, data given from palmprint or hand geometry present the advantage that they do not possess any low criterion compared to other modalities. Moreover, they are acquired from a single biometric modality which is hand trait. These advantages justify the choice of these modalities which are treated in this thesis.

2.2.6 Verification and identification

There are several kinds of applications which require users authentication. These applications may be classified into two categories namely identity verification and identification.

- Identity verification corresponds to verifying the claimed identity by comparing the acquired biometric data with its corresponding biometric templates stored in system database. In such system, a person who wants to be recognized claims an identity using a persons identification number or a smart card and the system conducts a one-to-one comparison to finally determine if the claim is true or false (by answering to this question: "Does this biometric data correspond really to Mr. Bob?"). Identity verification is an important task which aims to avoid the use of the same identity by various people [Wayman 2001].

TABLE 2.1: Comparisons of biometric modalities according to seven properties: Universality (U), Distinctiveness (D), Stability (S), Collectability (Co), Acceptance (A), Circumvention (Ci), Performance (P). ●●●:high degree, ●●:medium degree and ●:low degree.

Biometric modality	U	D	S	Co	A	Ci	P
Face	●●●	●	●●	●●●	●●●	●	●
Iris	●●●	●●●	●●●	●●	●	●	●●●
Fingerprint	●●	●●●	●●●	●●	●●	●●	●●●
Hand geometry	●●	●●	●●	●●●	●●	●●	●●
Palmprint	●●	●●●	●●●	●●	●●	●●	●●●
Keystroke	●	●	●	●●	●●	●●	●
Odor	●●●	●●●	●●●	●	●●	●	●
Retina	●●●	●●●	●●	●	●	●	●●●
Signature	●	●	●	●●●	●●●	●●●	●
Voice	●●	●	●	●●	●●●	●●●	●
Hand vein	●●	●●	●●	●●	●●	●	●●
DNA	●●●	●●●	●●●	●	●	●	●●●

- Identification corresponds to the fact that the system recognizes a person by searching all users templates stored in the database for matching. Thus, the system conducts a one-to-many comparison to build person's identity (or fails if a person is not enrolled in the system database) without need to claim their identity (by answering to this question: "To which person do these biometric data correspond?"). Identification is an important task for negative recognition applications, where the system determines if the person is who he/she denies to be. The aim of negative recognition is to avoid that a single individual uses various identities [Wayman 2001]. Identification may be used also in positive recognition for more convenience since the person does not need to claim an identity. On the other hand, traditional recognition methods (PINs, cards, etc.) may work correctly for positive recognition, negative recognition may only be determined via biometrics.

2.2.7 Structure of a biometric system

The structure of a biometric system consists of two different phases: enrollment and authentication, as shown in figure 2.2.

Enrollment is common for both verification and identification modes. It is the preliminary phase where the biometric data of a user is registered for the first time in the system. During this phase, one or more biometric modalities are captured and stored as templates in the database. This phase is very crucial since it influences, later, the whole recognition process. In fact, the quality of enrolled data is essential for ulterior identification phases because acquired data are considered as references for the person. A set of samples should be captured to take into account the variability of biometric modality of a person.

A biometric system is composed of 4 modules, some of them are common for enrollment and authentication phases namely acquisition, features extraction, matching and making decision. Acquisition and features extraction are two modules presented in enrollment and authentication phases. Features extraction is a data representation (e.g. image or signal) as a vector that should be representative for data and discriminant versus other data of other individuals. During enrollment phase, features vector extracted from the biometric sample is called reference and stored in database. During authentication phase, acquisition and features extraction modules allow to achieve a representation of biometric data to be tested later in features space.

Matching module is used during authentication phase to compare the feature vector extracted for test with the reference feature vector. The decision module consists in making a decision from output of matching module which generates a similarity score between two feature vectors. For verification applications, the matching is executed only once, between reference data and test data, and a decision of "true" or "false" is taken. For identification applications, the matching is carried out between all references stored in database and the decision is the answer

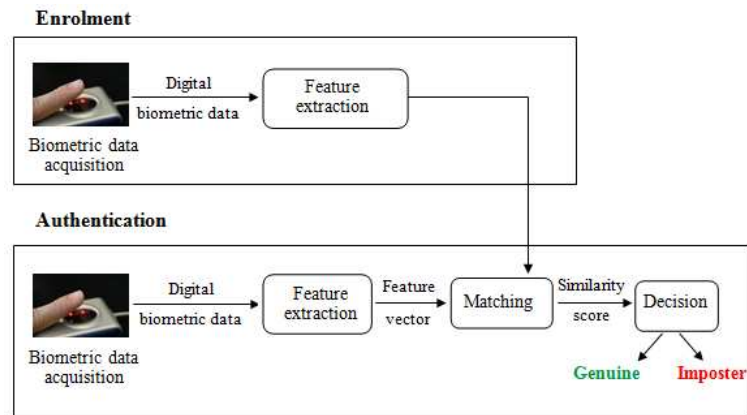


FIGURE 2.2: Structure of biometric systems

of the following question: "Does this person exist in the database, and if so, who is he/she?"

2.2.8 Evaluation of a biometric system

To evaluate the performance of a biometric system, three principal criteria have to be already defined clearly:

1. **False Rejection Rate** or **FRR**: This rate represents the percentage of individuals expected to be recognized but they are nevertheless rejected by the system.
2. **False Acceptance Rate** or **FAR**: This rate represents the percentage of individuals expected to be not recognized but they are nevertheless accepted by the system.
3. **Equal Error Rate** or **EER**: This rate represents the optimal performance measure and is computed depending on the first two criteria. It is achieved when $FAR = FRR$, i.e. the best trade-off between false rejections and false acceptances.

Figure 2.3 shows FAR and FRR diagram according to distributions of genuine and imposter scores. The EER is represented in Figure 2.4.

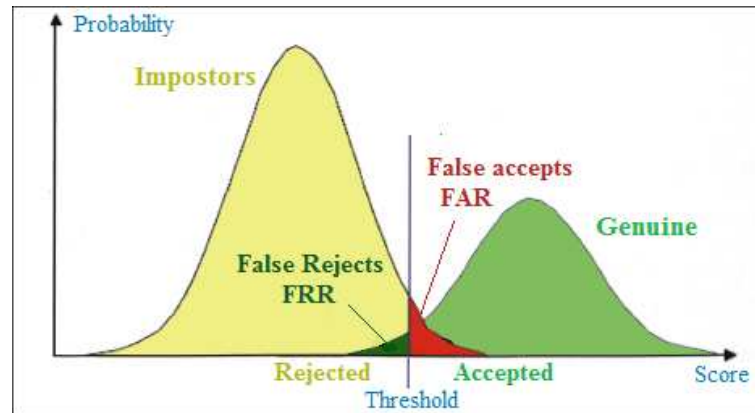


FIGURE 2.3: FAR and FRR diagram

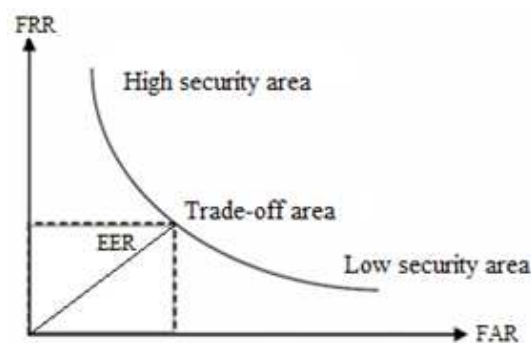


FIGURE 2.4: ROC curve

There are two ways to measure the biometric system performance, according to the mode (authentication or identification):

- If the system works in authentication mode, then the **ROC** (**R**eceiver **O**perating **C**haracteristic) curve is used. This curve draws the false rejection rate depending on the false acceptance rate. The more this curve fits the mark shape the more the system is efficient with a high Recognition Rate (RR).
- In the case of identification mode, the **CMC** (**C**umulative **M**atch **C**haracteristic) curve is used. The CMC curve provides the percentage of recognized individuals according to a variable called rank, as shown in figure 2.5. A system is said to recognize at the rank 1 when the nearest image is selected as the recognition result, and a system is said to recognize at the rank 2 when it

selects, among two images, the one that best matches the input image. Subsequently, the more the rank is high the more the correspondent recognition rate is related to a low security level.

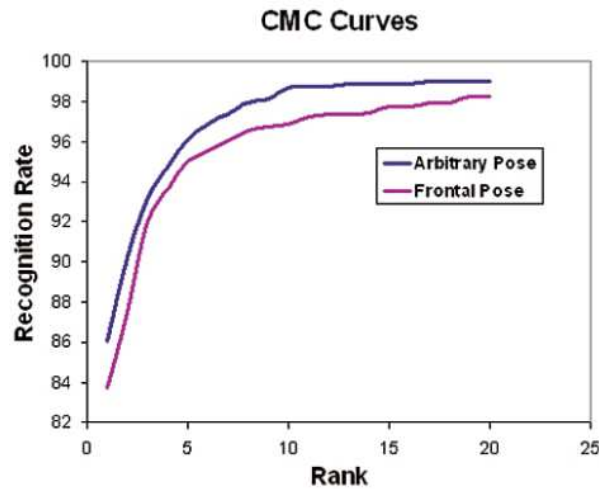


FIGURE 2.5: Example of CMC curves for different face poses used to identify a person based on his face [Buddharaju 2007]

2.3 Multimodality

Multimodality is defined as the use of several biometric systems. The principal purpose to fuse various biometric systems is to reduce the limitations of unimodal biometrics. Indeed, the combination of different biometric systems aims to enhance recognition performances by increasing the quantity of discriminant data of each person, and to reduce the risk of registration failure and the robustness to frauds.

2.3.1 Limitations of unimodal biometric systems

Biometry establishes a physical link between an individual and their identity and permits, hence, a more reliable identification than traditional ways like cards or keys. However, biometric systems have some limitations which prevent their use for all current applications. The main limitation incorporates performance. Despite possible security risks of traditional identification ways (loss, robbery or

falsification), they are 100% efficient in terms of recognition. If the password is correct, the response of system is "Right", otherwise, the response is "False", so the matching is 100% accurate.

However, biometric systems have not succeed so far to achieve this accurate recognition because they are based on a similarity score which is a real number describing the similarity degree between two biometric data. Therefore, the decision module is important for biometric system since a decision threshold has to be determined and applied to similarity score. If the score is higher than threshold value, the two samples are from the same individual and identity is well verified, otherwise, the two samples are from different individuals and the person is rejected (identity not verified). These variations in biometric data and the absence of an accurate matching are due to several factors:

- **Noise effect** in sensed data due to the imperfect conditions of data acquisition. Indeed, the captured biometric data could be noisy or distorted. In biometric information, variations (such as bad illumination or noisy acquisition) might generate inaccurate matching in database i.e. an imposter might be incorrectly accepted or an enrolled person could be incorrectly rejected.
- **Non universality**: although biometric traits are expected to exist among each single individual of a given population, there are some exceptions, in which an individual is not able to present their biometric trait because of pathological conditions, or working environments characterized by manual activities which may even erase fingerprint or palmprint data.
- **Temporal variability and non uniqueness** are also called intra-class variability (modality variation for an individual) and inter-class variability (variation between modalities of many individuals) may reduce the identification accuracy of biometric systems. For example, in the case of identical twins, the principal lines features of their palms may lead to inaccurate matching due to incorrect data inducing a false rejection.

- **Spoof attacks:** biometric systems are vulnerable to spoof attacks where the biometric trait may be imitated or forged. For instance, rubber fingerprints can be used for spoofing. In addition, less discriminative biometric traits are also prone to such attacks.

2.3.2 Different multi-types

Multimodal biometric systems reduce limitations of unimodal biometric systems by combining several systems. Five types of multimodal biometric system (figure 2.6) can be defined as follows:

- **Multi-sensors:** It consists in combining various sensors to acquire the same modality. For example, both optical sensor and multispectral sensor may be used for fingerprint acquisition.
- **Multi-instances:** It consists in combining several instances of the same biometric. For example, the acquisition of several images of face with different poses, expressions or illumination.
- **Multi-representations:** It consists in using several representations to treat the same image acquired. For example, the case of hand biometric which may be represented by its shape and its texture features.
- **Multi-samples:** It consists in combining various samples of the same modality. For example, two fingerprints of different fingers or two irises. In this case, different references have to be acquired in registration phase, unlike multi-instances which require a single reference.
- **Multi-biometrics:** It consists in fusing multiple biometric modalities such as hand geometry and palmprint.

A multimodal system may also combine these different types, for instance the fusion of face and prints of different fingers.

Each type of system has advantages and disadvantages and may overcome different

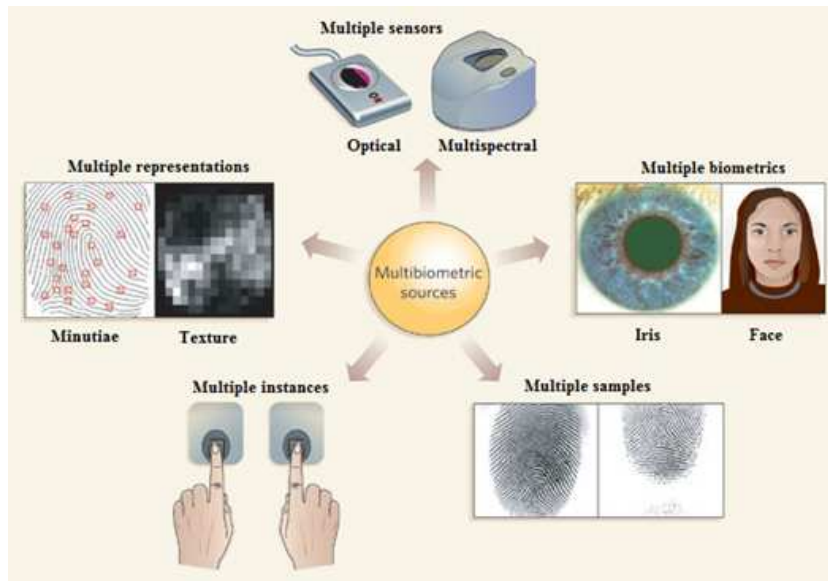


FIGURE 2.6: Different types of multimodal biometric systems [Jain 2007].

problems. The first four systems combine data from one and same modality that is not possible to resolve the problem of non-universality of some biometrics and fraud resistance, unlike multi-biometric systems.

In fact, systems which combine several data of the same biometric modality can improve recognition performances by reducing the effect of intra-class variability. Nevertheless, they are not able to resolve efficiently all problems of unimodal systems, and that is why researchers are more interested in their studies with multi-biometric systems.

2.3.3 Architectures of multimodal systems

Multimodal systems combine several biometric systems and require, therefore, the acquisition and processing of multiple data. The acquisition and processing may be done either successively, thus, we talk about serial architecture, or simultaneously, in this case we talk about architecture in parallel.

The architecture is mainly related to processing. In fact, biometric data acquisition is generally sequential for practical reasons because it is difficult to acquire a fingerprint and an iris image at the same time in good conditions. However, there are some cases where acquisitions may be performed simultaneously when

different data use the same captor, for example the sensors of multi-fingers may acquire simultaneously several fingerprints.

Hence, the architecture is generally related to processing and particularly of the decision phase. In fact, the difference between serial and parallel multimodal systems consists in obtaining a similarity score after each acquisition (serial fusion) or proceeding to all acquisitions before making decision (parallel fusion).

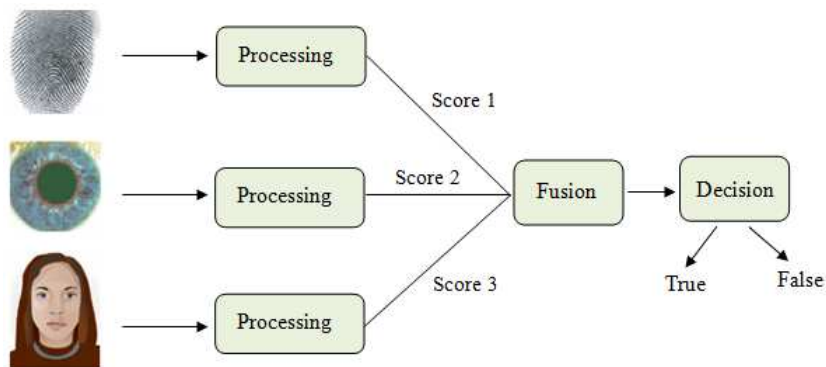


FIGURE 2.7: Architecture of fusion in parallel

The architecture in parallel type (figure 2.7) is the most used one because it allows employing all available data and, thus, improves performances of the system. However, acquisition and preprocessing of a large number of biometric data are costly either in terms of time or materials, and also reduce the convenience of use. Therefore, the serial architecture (figure 2.8) may be preferred in some applications for example it may overcome the problem of some individuals who are not able to present their fingerprint for authentication, thus, they can present their iris.

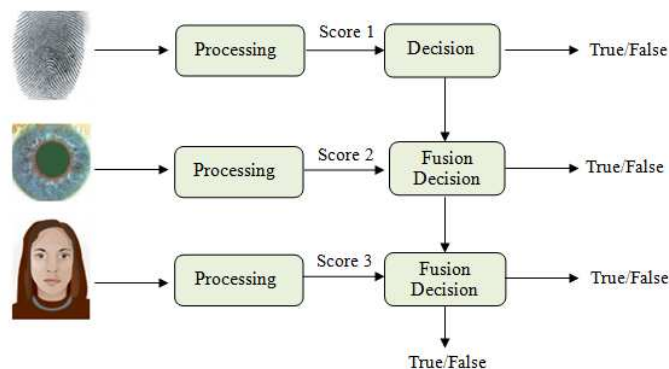


FIGURE 2.8: Architecture of fusion in series

Fusion of several biometric systems may take place at in four different levels: data level, extracted features level, matching score level and decision level (figure 2.9). These four levels may be classified into two subsets: pre-classification fusion (before matching) and post-classification fusion (after matching).

2.3.4 Fusion levels

In the literature, different modalities may be fused in order to improve accuracies of biometric systems. The fusion scheme may be performed in five different levels: data level, features level, matching score level, rank level and decision level, as detailed in figure 2.9. These five levels may be classified into two sub-categories namely fusion before matching step and fusion after matching step.

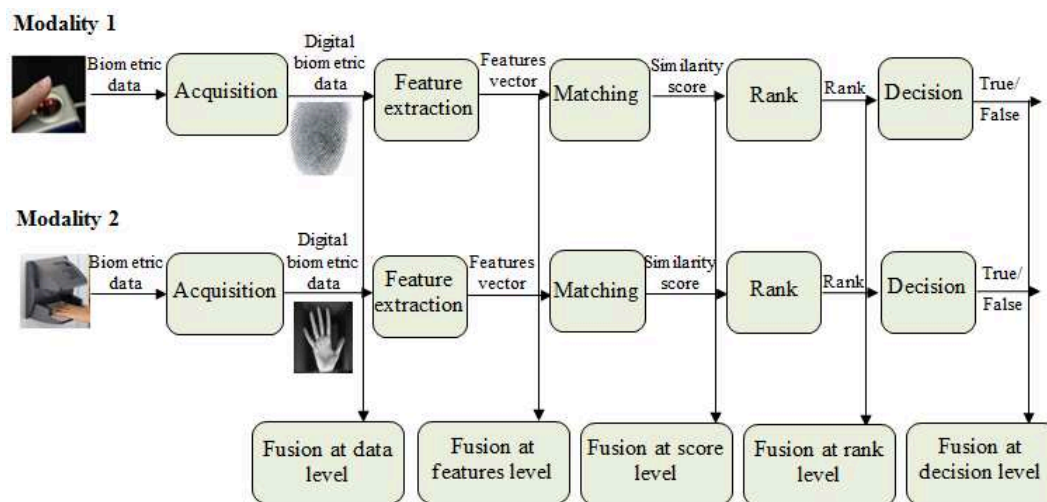


FIGURE 2.9: Different fusion levels of biometric systems

2.3.4.1 Fusion before matching

Before matching step, the integration of information may be whether at sensor level or at feature level, after feature extraction module.

- Fusion at sensor level

The fusion at sensor level is the first level of fusion. The aim of this fusion is

to generate a new capture, with better quality than the sources captures, to be treated before feature extraction. This technique is called image fusion or pixel fusion in the image processing area. Such fusion is relatively rarely used because it requires homogeneous data. Indeed, the fusion at sensor level may be performed using various compatible captures of instances derived from the same biometric trait, or several instances of the same biometric trait detected from a single sensor. The data fusion is generally not possible if the instances of the data are incompatible.

- Fusion at feature level

The fusion at feature level incorporates combining different feature vectors (figure) which may be obtained either from different instances of the same biometric trait or from different biomtric modalities.

The aim of such fusion is to obtain robust features in the case of homogeneous data (i.e., derived from the same modality with the same feature extraction method), or containing more information in the case of heterogeneous data (i.e., from different modalities or with different feature extraction methods). In the case of homogeneous data, the simplest way to fuse attributes is to

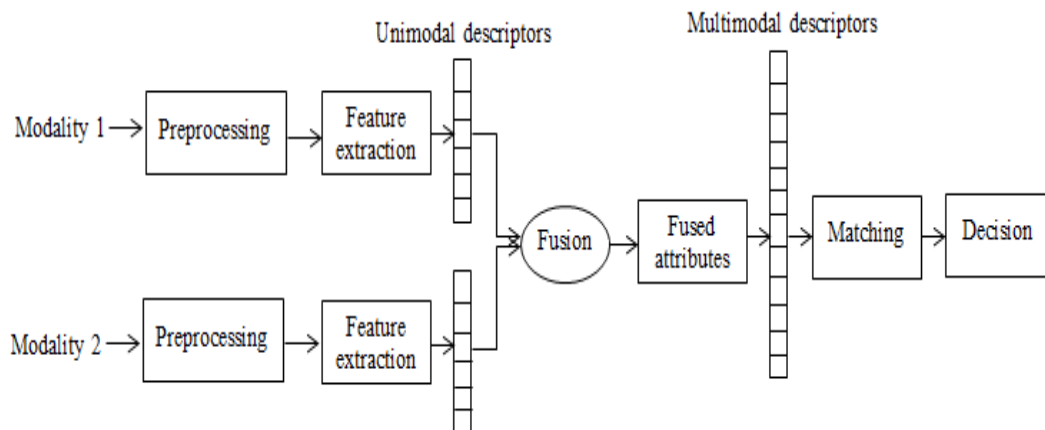


FIGURE 2.10: Flowchart of general fusion at feature level.

concatenate them. This supplies a vector of larger size, which contains more information (as shown in figure 2.11). However, in the case of heterogeneous data, a normalization step (data standardization) should be made before vectors concatenation.

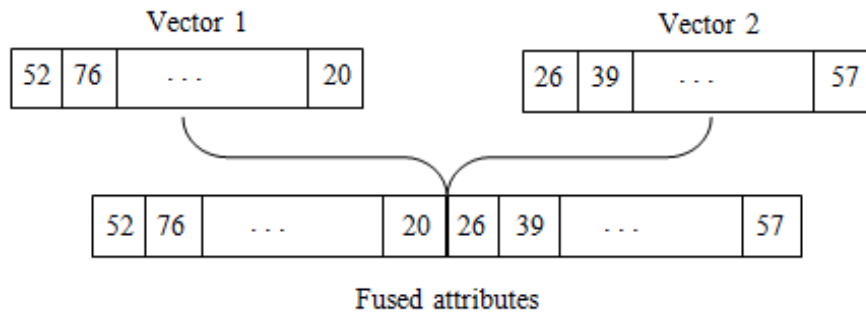


FIGURE 2.11: Concatenation of attribute vectors.

To deal with high dimensionality of feature vectors obtained after fusion, it is useful to reduce its dimension using a statistical analysis applied on the concatenated vector or by the selection of the most relevant attributes. The dimensionality reduction step involves additional cost and time.

2.3.4.2 Fusion after matching

The fusion after matching step is based principally on classifiers fusion. In fact, this fusion type is the most studied one by researchers. Such a fusion may be performed at score level, at rank level or at decision level.

- Fusion at score level

Fusion at score level is referred to as the combination of similarity scores derived from different classifiers. This type of fusion is the most commonly used one since it may be applied to all types of systems (contrary to the fusion before matching), in a small dimension space (the size of the vector of scores represents the number of sub-systems), using relatively simple and effective methods and treating more information than decision fusion. Indeed, the fusion at level score presents the best trade-off between information richness and ease of implementation.

There are two approaches to combine scores obtained from different classifiers. The first one embodies treating this as a classification problem which searches to separate the two classes Genuine and Impostor in the N dimensional space of scores. The second one comprises treating the subject

as a combination problem in which the scores are treated separately before combination to achieve the final score.

In the classification approach, a feature vector is built using the matching scores given by each classifier apart. This vector is, then, assigned to the second classification level based on two classes: "accepted" or "rejected". It is noted that the scores obtained from different modalities may be non-homogeneous (distance measure or similarity, different ranges of values, etc.) Various classifiers may be used such as Neural Networks, Support Vector Machines (SVM), decision trees, Bayesian networks, . . .

- Fusion at rank level

The fusion at rank level concerns the identification of a person among all allowed persons. In fact, the identification process of each sub-system returns the list of identity classes in descending order of confidence. It is noticed that these rankings may be compared directly, even if they are provided from different modalities. Accordingly, the normalization process of data is not required, which facilitates the implementation of this type of fusion.

Ho et al. [[Ho 1994](#)] described three methods to combine the ranks provided by the different classifiers. These methods includes the highest rank method, the borda count method and the logistic regression (or weighted borda count) method. The highest rank method assigns to each possible matching the best (minimum) rank computed by the different classifiers. However, even if only one sub-system classes properly the user to be identified, with a good confidence index, the overall system should give this user a fairly high rank.

The borda count method is based on a weighted voting process, by the sum of ranks assigned to each possible matching. The advantage of this method compared to the highest rank method is the ability to consider variability between ranks even with a large number of classifiers. However, the borda count method assumes that classifiers are statistically independent and each one of them provides good results, which makes the borda count method vulnerable to the effect of weak classifiers.

The logistic regression or weighted borda count method is a generalization of borda count method which uses statistical knowledge about the performance of sub-systems. Indeed, it assigns a different weight to each sub-system, depending on its effectiveness. These weights are computed during a learning phase, by a logistic regression. This method presents the advantage to take into account the differences of efficiency between different sub-systems.

Other methods have been also presented for rank level fusion such as the method of Saranli and Demirekler [Saranli 2001] that includes the three previous methods, and the method of Nandakumar et al. [] which is based on the Bayesian approach.

- Fusion at decision level

It is the most abstract level of decision in a multi modality system. Indeed, each system provides a binary decision in YES or NO form and the system of decisions is to take a final decision according to a set of decisions. Generally, the methods are based on votes such as 'OR' and 'AND' [Ross 2007]. The first one consists of accepting the client if at least one sub-system recognized the user. It is suitable for systems that can tolerate a low security. However, the second one consists to accept the client if and only if all systems recognized the user [Ross 2007]. Thus, it is suitable only for high security systems. The two previous methods are very simple, but rarely used. Indeed, they degrade the performance of biometric multi-system in terms of EER. The majority voting [Lam 1997] generates the final decision based on the number of votes provided from each classifier. This method requires no training phase, and no prior knowledge about the different sub-systems. On the other hand, performances of sub-systems should be comparable. Otherwise, a solution based on weighting the decision of each sub-system may be employed by assigning a higher weight to the most reliable sub-systems and this method is called weighted voting [Kuncheva 2004]. Other complex methods, based on prior information regarding the performances of various biometric sub-systems and presence of training phase, exist. For example, we can cite methods based on Bayes theory [Xu 1992], the evidence theory

of Dempster-Shafer [Xu 1992], the behavior knowledge space [Huang 1995], etc. To conclude, all fusion methods at the decisions levels require less computational complexity and less execution time, but use very little information (0 or 1).

2.4 Why hand modality ?

The hand trait presents various advantages compared to other biometric modalities. In fact, it is considered as attractive for the following reasons:

- The simplicity of hand acquisition with inexpensive devices [Kumar 2006a],
- The hand information may be extracted using low resolution images [Sidlauskas 1994],
- The hand trait is more acceptable by the public compared to other modalities [Kukula 2006],
- The additional biometric modalities including palmprints and fingers may be embedded in a developed hand shape biometric system [Kumar 2006a, Yoruk 2006b].

2.4.1 Presentation of some biometric modalities of the hand

Several hand recognition systems, which describe the different parts of the hand making the person's identity, have been proposed. This section presents some hand characteristics, namely hand shape, hand geometry, palmprint and fingers.

2.4.1.1 The hand Shape/geometry

The hand shape (or the silhouette of the hand, as presented in figure 2.12) has been given little interest in the literature, in order to recognize individuals, in spite of the important amount of research work proposed on shape matching in the field of



FIGURE 2.12: Hand shape.

computer vision. Historically speaking, Jain and Duta [[Jain 1999a](#)] were the first to analyze deformable shape and develop a method in which hand shapes are stored and compared according to the mean alignment error. The main advantage of this modality is that it is simple and easy to capture. Besides, it is not very sensitive to the state of the hand, i.e., dirt and cuts will not prevent the functioning of the system. However, it also presents defects which may make the system inaccurate. In fact, different individuals may have almost similar hand shapes. Furthermore, jewelry and accessories may represent a challenge for extracting the hand shape information.

Hand geometry has also received much attention for hand biometrics. Also called "hand measurements" in the literature, geometrical features present the principal features of the hand geometry which are adopted in the majority of hand biometric systems. These features have the merit to be relatively invariant to orientations of the fingers and the global hand positioning. Among these different geometrical measurements, we may mention the size of the palm, the length of the hand or fingers, the width and perimeters of hand and fingers, etc. [[Guo 2012](#)], as displayed in figure [2.13](#). For example, Luque-Baena et al. [[Luque-Baena 2013](#)] have extracted 403 geometrical features, including areas, perimeters, rectangularity measure, compactness, aspect proportion, etc. In fact, this is the highest number adopted in the literature in order to improve performances of the person recognition system. Although geometrical features are easy to extract, they are not sufficiently discriminating to be utilized for identification/verification tasks in high security. Actually, the information of the hand shape is limited only to a subset of features and the texture information cannot be employed. Therefore, some

authors suggest the fusion of geometrical features with other hand characteristics such as palmprint features [Kumar 2006a] or finger shapes [Oden 2003].

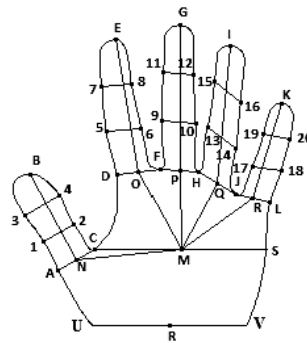


FIGURE 2.13: Hand geometry features.

2.4.1.2 The palmprint

The palmprint is one of the most commonly used biometric recognition techniques especially for criminality. The palmprint presents the inner part of the hand (the invisible part when the hand is closed) from the wrist to the finger roots (figure 2.14). It was defined in previous systems as the print of the palm by its pressure on a given surface. In other words, it can be defined as palm template illustrating the physical features of the skin pattern [Kumar 2009]. The usage of palmprint features in the identification process was initially proposed by Shu and Zhang [Shu 1998].

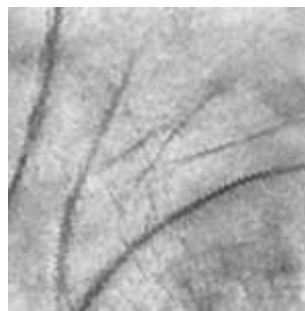


FIGURE 2.14: Palmprint region.

Palmprint modality may present different kinds of features that can be exploited for the person recognition [Shu 1998, Panigrahy 2008]: (1) principal lines, (2)

wrinkles or secondary creases and (3) ridges. All these features may characterize a person since they are discriminant and stable over time. Concerning wrinkles or secondary lines, they are thinner and more irregular than principal lines. Regarding ridges such as minutiae of fingerprints, they are very thin and regular. A high resolution imaging is required for a good minutiae extraction [Lu 2003].

2.4.1.3 The fingers

The hand shape varies from one person to another due to the articulation of fingers. Accordingly, some researchers have proposed to segment fingers from the hand to separately model finger shapes (figure 2.15). Oden et al. [Oden 2003] have proposed to model the shape of each person's finger using implicit fourth degree polynomial functions. Moreover, Keren invariants were extracted from the fitted polynomials so as to be utilized as a feature invariant to affine transformations [Keren 1994]. However, Ribaric and Fratric [Ribaric 2005] segmented the hand into six sub-images describing the palm region and 5 finger surfaces. From these sub-images, the most important features are extracted on the basis of Karhunen-Loeve transform to acquire eigenfingers which are fused to eigenpalms. In another work, Xiong et al. [Xiong 2005] identified multiple fingers aligned according to an elliptical model, by Euclidean transformations.



FIGURE 2.15: Five finger surfaces.

2.4.2 Principal challenges of hand modality

The hand shape trait is a biometric modality designed for medium security applications. Therefore, it suffers from various challenges described as follows:

1. Challenges based on environmental conditions

It concerns the background variation and lighting conditions changes (low/high illumination). In fact, they are very substantial challenges for hand shape and palmprint recognition systems. Some examples of environmental condition challenges are shown in figure 2.16.



FIGURE 2.16: Some examples of environmental challenges.

2. Challenges based on acquisition

Acquisition may cause noising due to pressure of users on glass plate or deformations ascribed to contactless acquisition devices. In fact, performances of a biometric system are sensitive to samples quality and variations. Hence, noisy samples may affect the accuracy of the system. Figure 2.17 demonstrates some examples of acquisition challenges.



FIGURE 2.17: Some examples of acquisition challenges.

3. Challenges based on occlusions

The hand is an articulated object having many liberty degrees. Indeed, the occlusions may include folded fingers, a closed fist, a closed palm not parallel to the image plane. In addition, the hand size may change; position and orientation affect the clarity of the regions of interest of the palmprint or the finger regions. The presence of artifacts such as rings, bracelets, etc. is also one of unavoidable difficulties in the case of a free use. Figure 2.18 reports some examples of occlusion challenges.



FIGURE 2.18: Some examples of occlusion challenges.

4. Challenges based on execution time: biometric recognition systems grounded on hand modality have to generate person's decision as a low time as possible to facilitate their use in real time applications.

The satisfaction of all these challenges, simultaneously, is difficult. Therefore, some facilities may be made according to the intended use by imposing some restrictions for users or environmental limits.

2.5 Conclusion

In this chapter, we have chiefly described the general context of biometry by describing the different biometric modalities, the limitations of unimodal systems and the advantages of multimodal biometrics. Subsequently, we have dealt with the advantages and the challenges of hand biometric trait. The following chapter will introduce a survey and an overview of different unimodal and multimodal biometric recognition methods based on hand shape and palmprint modalities that are presented in the literature.

Chapter 3

Hand shape and palmprint modalities: a survey

Contents

3.1	Introduction	39
3.2	Hand Shape Modality	39
3.2.1	Hand image acquisition	39
3.2.2	Hand detection	43
3.2.2.1	Active contour	43
3.2.2.2	Active Shape Model (ASM)	45
3.2.2.3	Active Appearance Model (AAM)	46
3.2.2.4	Hand segmentation	47
3.2.3	Hand feature extraction	48
3.2.3.1	Feature-based hand geometry	48
3.2.3.2	Feature-based hand shape and texture	49
3.2.3.3	Feature-based hand contour	49
3.2.4	Matching module	50
3.2.5	Decision-making module	50
3.2.6	Discussion and overview of different hand shape approaches	51
3.3	Palmprint modality	54
3.3.1	Characteristics of palmprint modality	54
3.3.2	Palmprint image acquisition	55
3.3.3	Palmprint Region Of Interest (ROI) extraction	57

3.3.4	Palmprint feature extraction	59
3.3.4.1	Local approaches	59
3.3.4.2	Global approaches	61
3.3.5	Overview of different palmprint approaches	63
3.4	Multimodal hand shape and palmprint biometrics . .	66
3.4.1	Challenges of using multimodality	66
3.4.2	Design of multimodal biometric systems	66
3.4.3	Overview and discussion of hand shape and palmprint fusion approaches	67
3.5	Conclusion	69

3.1 Introduction

Hand-shape modality is a physical biometric trait employed to characterize a person using their hand silhouette or/and geometric features such as finger lengths and widths, areas, perimeters, ratios, extracted from hand images. Compared to other biometrical traits, the measurement of hand shape is simpler to achieve with fast calculation. Historically speaking, hand geometry systems had longer implementation history than many other biometric modalities since they were firstly proposed by Ernst in 1971 [Ernst 1971].

This chapter exhibits the different steps of a general hand biometric system as well as an overview of hand shape modality, palmprint modality and multimodal hand shape and palmprint approaches proposed in the literature.

3.2 Hand Shape Modality

A general model of hand recognition system is illustrated in Figure 3.1. To ensure the persons verification, five steps are required including image acquisition, hand detection, feature extraction, matching module and decision-making module. Each step is described in the following subsections.

3.2.1 Hand image acquisition

The acquisition of hand images may be achieved by placing the hand in front of a simple device such as a commercial scanner, a Webcam or a standard optical camera with low/medium resolution. Most of the system devices furnish their own illumination to have better quality of images with ambient lighting [Kumar 2006a], or use the infrared light [Morales 2008] (figure 3.2) to solve the segmentation problems of the hand in a real environment. The earlier studies of commercial systems [Sidlauskas 1988, Sidlauskas 1994] and research studies [Jain 1999a, Sanchez-Reillo 2000, Kumar 2006a, Golfarelli 1997, Jain 1999b]

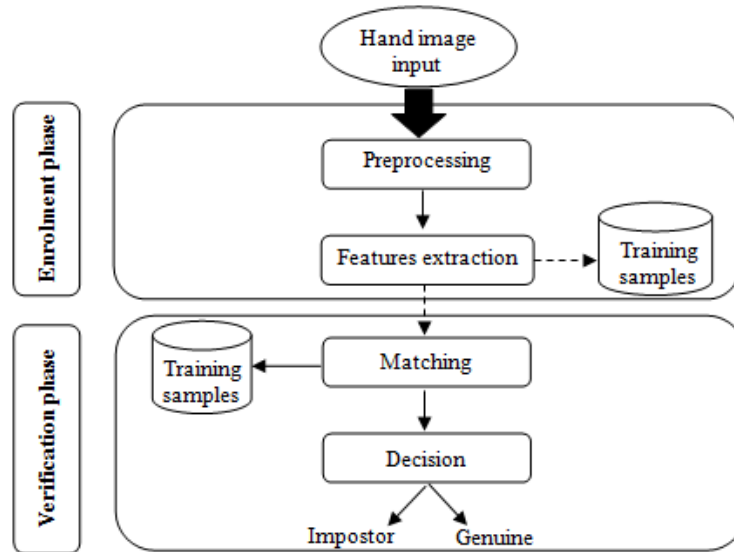


FIGURE 3.1: General hand recognition process.

integrated pins on the platform of the device to fix the placement of the hand. Later on, several researchers indicated that these pins caused the deformation of the hand shape and limited the hand placement, which can reduce user convenience. Therefore, various devices have been proposed without any guidance and any contact to freely acquire hand images [Xiong 2005, Guo 2012, Yoruk 2006b, Adan 2008, Dutagaci 2006, Amayeh 2006, Morales 2008]. The most widely used and public hand datasets are summarized in Table 3.1 and described as follows:

- IITD hand database:** it is based on hand images collected from the students and staff at IIT Delhi, New Delhi, India. IITD is a public contact-free hand database [Kumar 2008, Kumar 2011a] which contains 1150 hand images. They are acquired using a digital CMOS camera from 235 subjects. The images are acquired in different hand pose variations and collected in an indoor environment employing a circular fluorescent illumination around the camera lens. Five samples are captured from left hand at different times. All images are in bitmap format with a resolution of 800×600 . Moreover, palmprint images are automatically cropped and normalized in 150×150 pixels.







- **GPDS150 hand database:** It is a public database [Ferrer 2007] in which hand images are collected from 150 users with 10 different acquisitions using a desk scanner. These images have been captured from the right hand of subjects. The placement of the hand is free over the acquisition surface; no restrictions (templates or pegs) are imposed on users to acquire their hands. The segmented palms as well as the contour of the hand with landmarks (tips and valleys of the fingers) are also provided. All images are in jpeg format, 120 dpi of resolution and 256 gray levels.
- **Bosphorus hand database:** It is created at the Bogazici University [Yoruk 2006b] and intended for hand biometry research. Hand images are acquired from more than 600 subjects varying from 20–50 years old, in different intra-class pose variations. Six hand images per person in which three left hand images and three right hand images are collected from each person at three different sessions using an HP Scanjet 5300c scanner. All images are in bitmap format with a resolution of 383×526 .
- **Biosecure multimodal biometric database:** It has been developed in order to integrate data related to several biometric modalities including face, iris, hand, voice and signature. Concerning hand biometric modality, the acquisition is performed using a Canon Eos camera from 750 subjects with 6 acquisitions for each subject. The resolution of images is of 2336×3504 .

Some examples of acquisition devices are exhibited in figure 3.2.



FIGURE 3.2: Examples of hand acquisition devices [Morales 2008, Kumar 2006a].

TABLE 3.1: Some hand databases existing in the literature.

	GPDS ¹	IITD hand DB ²	Bosphorus hand BD ³	Biosecure ⁴	Amayeh et al [Amayeh 2009]	Guo et al [Guo 2012]
Year	2005	2006	2006	2007	2009	2012
Number of subjects	150	235	642	750	101	100
Number of samples	10	5	6	6	10	60
Number of images	1500	1175	3852	4500	1010	6000
Gray/Color	Gray scale	Gray scale	Gray scale	Color	Gray scale	Color
Resolution	1403×1021	800×600	382×525	2336×3504	480×640	640×480
Illumination	Non controlled	Semi controlled	Non controlled	Controlled	Controlled	Non controlled
Accessories	N/A	Rings	Rings, bracelets, watches	Rings, bracelets	N/A	N/A
Devices	Hp scanner	Camera	Commercial scanner	Canon Eos 30D	VGA resolution CCD camera	Webcam + infrared filter
Origin	Spanish	Indian	Turkish	French	American	Taiwanese
Examples						

¹www.gpds.ulpgc.es²www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Palm.htm³bosphorus.ee.boun.edu.tr/hand/Home.aspx⁴biosecure.it–sudparis.eu

3.2.2 Hand detection

Contour detection is a major key in object recognition field. Actually, a contour represents, broadly, a border between adjacent areas in an image, having distinctive brightness (or textures or colors). Indeed, edge detection techniques often analyze the global image without taking into account the characteristics of its different regions. Thus, the contours of the same image may be well detected in some areas and poorly detected in others. To overcome this problem, it is necessary to study some contour detection approaches and analyze their performances [Missaoui 2005].

With regard to hand object detection, several methods have been proposed in the literature and classified into skin color based methods and shape based methods. However, the skin color may be exposed to some variations due to illumination and background changes during acquisition. Therefore, we focus on hand detection approaches founded on shape namely active contour based methods, active shape model based methods and shape context based method.

3.2.2.1 Active contour

Active contour is a segmentation method proposed by Kass et al. [Kass 1988] in 1988. It is based on contour detection in an image called active contours (or snake). In fact, the principle of active contours is to evolve an initial curve towards the object of interest. This curve is represented as a set of points in which the number of points vary according to the desired accuracy (figure 3.3).

At the beginning, the contour is localized uniformly around the object of interest. Thereafter, it will retract in order to follow the shapes as well as possible. Similarly, an active contour may also dilate and try to fill the shape, thus, it will be located inside. At each iteration, the algorithm will attempt to find the best position for the contour in order to minimize derivatives according to the used constraints. The algorithm stops when it is no possible to improve the position of the contour or when the maximum number of iteration has been reached. Accordingly, the concepts

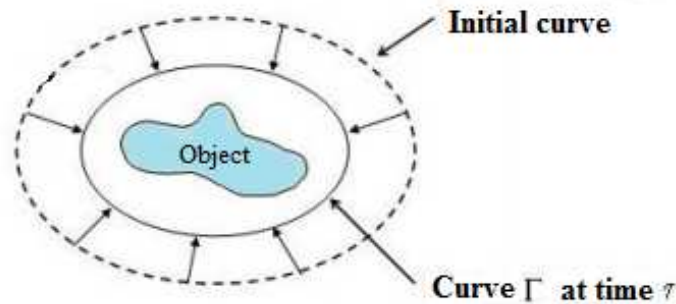


FIGURE 3.3: Evolution of active contour $\Gamma(\tau)$ toward the object of interest [Lamard 2010].

of internal and external energies are used in order to characterize, respectively, the contour shape and the position of the contour on the image by taking into account the gradient lines.

These concepts are represented as the energy E given by the following equation:

$$E_{snake}(C) = E_{int}(C) + E_{ext}(C) + E_{img}(C) \quad (3.1)$$

Where E_{int} is the internal energy related to the curve features such as height, curvature, etc. and E_{ext} is the external energy related to additional constraints imposed by user in order to achieve the desired contour, such as minimum radius, etc. However, E_{img} represents the energy imposed by the image such as energy of gradient, energy of intensity, etc. and C is the active contour curve. The purpose of active contour is to minimize this energy E_{snake} until stabilization on minimum local of its energy corresponding to the shape of the object of interest.

In hand recognition field, the work of D'Ornellas [D'Ornellas 2006] may be cited. In fact, it has improved the snake technique in order to segment the hand for biometric recognition using the hand shape. This improvement was based on adding more nodes and the removal of redundant nodes in order to describe the complexity of the extracted contour. The inserted and removed nodes are based on the energy analysis of the active contour algorithm. The dynamic handling related to the number of nodes allows a better capture and track of the hand geometry.

3.2.2.2 Active Shape Model (ASM)

Active Shape Models (ASM) were originally introduced by Cootes and Taylor in 1992 [Cootes 1992], so as to locate deformable objects in medical images. They have been then extended to hand segmentation, hand tracking, face segmentation, etc. In fact, they are statistical shape models of an object which are iteratively deformed to be adjusted to a copy of this object in a new image. Active shape models are based on a statistical training from shapes set to achieve a model of global variations. This global model is named Point Distribution Model (PDM) which is deformed, in the image to be segmented, until fitting the object to be detected. To build the ASM, an images database of the object of interest is provided with different possible variations. Each object is manually labeled by a set of feature points or "landmarks". Hence, each shape will be represented as a predefined number of points depending on the object complexity and the desired level of description. Furthermore, the active models use an iterative algorithm for translating, rotating and scaling point sets in order to align them. This alignment eliminates laying variations and maintains only shape variations. Thereafter, active models apply the Principal Component Analysis (PCA) on the set of aligned shapes in order to find the mean position of points and the principal variation directions. Once the training is performed, the shape contour to be segmented in the new image is localized using an iterative algorithm [Cootes 1995]. Nevertheless, the discrimination of this method depends highly on the training set representation. In addition, the manually labeling step is consuming and the initialization phase affects its efficiency i.e. if the ASM is badly positioned upon initialization, it will not converge to the object of interest. Therefore, the correct normalization is required in order to ensure the convergence of this algorithm.

Regarding hand recognition field, the active shape models have been used by Yuan and Barner [Yuan 2006] in the context of the hand gesture recognition. The purpose of this approach is the classification of hand gestures via their shape contour. The training of hand shape models is performed through a sequence of hand shapes in which the contour is obtained. Indeed, the contour is represented as a vector

formed by a fixed number of points. It is then classified and compared to the best similar model using Euclidean distance. However, positioning, scaling and rotating are different among various extracted hand shapes. Therefore, an alignment phase is applied to the shapes set using Procrustes analysis. After alignment, the deviation within the shapes is represented and the principal component analysis (PCA) is employed on this deviation in order to achieve the mean shape. Finally, to localize the contour of the tested hand image, an iterative algorithm is used in order to deform the mean shape. The convergence is reached after 92 iterations. The classification phase is then performed using Support Vector Machines (SVM) through the ASMs as prior information, for gesture classification. Experiments have demonstrated good recognition rate compared to feature based approaches.

3.2.2.3 Active Appearance Model (AAM)

Active Appearance Model (AAM) represents an extension of active shape models (ASM) introduced also by Cootes et al. [Cootes 1998]. They have the property to consider, additionally, texture information as well as the shape. Furthermore, each information inside the object region is taken into account rather than taking only modeled edges. The AAMs are based, primarily, on the construction of shape variation model as in ASMs and secondly on the construction of texture variation model. Finally, these two models are concatenated in order to obtain a single appearance model.

Using the active appearance model, Teng et al. [Teng 2005] suggested a method for hand appearance identification based on AAM. In fact, to build the AAM, a training data including N images is necessary, in which n feature points are manually labeled on the contour of the hand. With respect to testing data, the authors employed Mahalanobis distance so as to classify hand appearance images for user verification. Results obtained are promising and compared to other existing methods.

On the other hand, Gross et al. [Gross 2007] proposed a robust hand geometry method for persons identification using active appearance model. Actually, the

AAM is built in order to track the hands of persons. According to the landmark points localized on the hand given from the fitted AAM (employed to update the position of the model in each sample), the geometrical features of the hand are extracted for persons identification. These features are then compared to the hand database. Results obtained are promising with an identification accuracy in excess of 90% using only five characteristics.

The study and application of these models bring out some inconveniences. As active shape model, the discrimination power of this method is directly depending on the representation of training set. In addition, the manually labeling task of training set images is tedious and time consuming especially for high training sets, which is necessary to construct the good model. Moreover, the annotation has to be performed with the highest possible precision, by an expert for example. Nevertheless, imprecision of feature point positions may not be excluded definitively, which induces uncontrolled errors in the final model. On the other hand, the dependence in initialization is another inconvenience. In fact, the position of the object of interest should be known in advance. This problem may be partially resolved by using a multi resolution method, but a preliminary localization step is required for guaranteed results.

3.2.2.4 Hand segmentation

The aim of hand segmentation as other hand detection methods, is to extract the hand region from background. Indeed, the segmentation of a two-object scene, which consists of the hand and the background is not a difficult task. Nonetheless, many factors may affect badly the segmentation accuracy such as artifacts due to wristwatch or overlapping cuffs, rings, or creases around the boundaries because of too much light or heavy pressing. Moreover, the tracking of the hand has to be very accurate and appropriate, since the variations between hands of different persons are usually thin. Thus, it is necessary to segment the hand shape accurately in order to maintain the discrimination between subjects. To reach that, several techniques for hand shape segmentation are employed by researchers. Indeed,

constrained by fixed pegs, the authors in [Jain 1999a] employed the mean-shift unsupervised segmentation method followed by a contour detection algorithm in order to calculate the hand shape. On the other hand, constrained by other circumstances during image acquisition, Amayeh et al. [Amayeh 2009] have firstly fixed a threshold value for the extraction of silhouettes of hand and arm, and secondly applied a morphological closing method in order to crop the arm region and maintain only hand shape part.

Regarding peg-free and contact-free modes, some authors [Hu 2012, Kumar 2003, Ferrer 2011] employed OTSU thresholding algorithm for segmentation and encouraging results were achieved. However, these works have not considered different factors like accessories (watches, bracelets and rings), or some artifacts of dirty hands, which have a bad effect on segmentation performance using simply thresholding algorithms. To overcome this issue, researchers [Yoruk 2006b, Dutagaci 2008] employed the K-means clustering method for RGB color images and morphological correction methods followed by ring removal algorithm in order to separate the hand from the background.

3.2.3 Hand feature extraction

3.2.3.1 Feature-based hand geometry

A set of characteristics describing the hand shape may be extracted from hand images. Generally, the most widely used characteristics discriminating the shape of the hand are geometrical measurements such as hand length, finger lengths and widths, aspect ratio of the hand or fingers, surface, etc. To compute these distances, some researchers have proposed to model the hand shape based on a set of points located as a set of 2-D coordinates, including five tips and four valleys of the hand. In the literature, the number of geometric characteristics has varied mostly between 11 and 40 [Sanchez-Reillo 2000, Kang 2014, Yuan 2011], while Luque-baena et al extracted 403 geometrical features from fingers and hand shape separately [Luque-Baena 2013].

3.2.3.2 Feature-based hand shape and texture

Some research works have defined other type of features in order to describe the hand shape. In fact, various features are extracted from both shape information and texture information [Yoruk 2006b], namely Independent Component Analysis (ICA) features, Principal Component Analysis (PCA) features and Angular Radial Transform (ART). These features show good performances for hand biometrics. In fact, ICA is a technique in which independent variables are statistically extracted from a mixture of them. Yoruk et al. [Yoruk 2006b] applied ICA analysis tool alternately on binary silhouette images in order to extract the prototype of shape information and the appearance data forming shape and texture information. On the other hand, PCA is a statistical technique which employs an orthogonal transformation in order to convert a set of observations of correlated variables into a set of values of linearly uncorrelated variables named principal components. For hand biometrics [Yoruk 2006b], a set of landmark points localized on the contour of the hand is represented as variables for PCA features extraction. ART features have also been extracted to describe the edge of the hand, in the work of Yoruk et al. [Yoruk 2006b]. Indeed, this transform is defined as the region-based shape descriptor which describes the distribution of pixels in a region or an object. Hence, the ART coefficients are represented as polar coordinates of the hand contour.

3.2.3.3 Feature-based hand contour

Hu et al. [Hu 2012] proposed a hand shape recognition method based on Coherent Distance Shape Contexts (CDSC) which are grounded, in their turn, on Shape Contexts (SC) and Inner-distance Shape Contexts (IDSC). These features (CDSC) are extracted principally from fingers contour and present several advantages. In fact, discriminative features from hand shape are captured, moreover, they can overcome the problem of inexact matching between landmark points of the hand. Thus, these descriptors are robust to hand poses and different deformations of fingers.

3.2.4 Matching module

The matching step incorporates the comparison of feature vectors extracted from a claimed person to samples stored in the database on the one hand, and the computation of the matching score (or similarity score) on the other hand. This score can be generally calculated using various metric distances such as Euclidean distance [Sanchez-Reillo 2000, Amayeh 2006], Mahalanobis distance [Pavesic 2004], correlation coefficient [Kumar 2006a, Park 2013], absolute distance (L1) [Yoruk 2006b] or combining these different distances in the case of multimodal biometric systems [Pavesic 2004].

The matching score is a measure of similarity between the hand image of a claimed user and the samples stored in database. With respect to the shape of the hand, different people may have similar hand shapes and this possibility increases especially with a large population. Therefore, different approaches have been suggested in the literature to correctly envisage the identity of the person. For example, researchers have proposed to train a set of classifiers using the support vector machines (SVM) since this technique mostly provides better generalization performance [Morales 2008, Goh 2012, Ferrer 2011]. The idea is to train a classifier for each enrolled person by considering the set of feature vectors associated with the input person as positive templates, and the other feature vectors as negative templates. The matching score is produced using the trained classifier.

3.2.5 Decision-making module

According to the previously computed matching score, the final decision about the identity of the person (identification) or the person who claims his/her identity (verification) is made. In verification mode, a specific threshold value is chosen. In fact, if the matching score is above the threshold value (hand images from the same person), the person is accepted, otherwise he/she is rejected. The threshold value is selected depending on some important rates i.e. the equivalence of False Acceptance Rate (FAR) and False Rejection Rate (FRR), which provide the Equal

Error Rate (EER). In identification mode, the input feature vector is affected by the identity of the nearest template stored in database. If the distance is less than the verification threshold, the claimed identity is considered as genuine, otherwise it is considered as an impostor.

3.2.6 Discussion and overview of different hand shape approaches

A brief study of different hand shape approaches for person recognition is presented. Considering this study, various hand databases have been summarized in section 3.2.1. We also displayed several methods for hand contour detection, such as active contour, active shape model and active appearance model. These methods are robust to illumination changes, however, they are complex and require much time, which is against the objectives of biometric systems. Moreover, they are not robust to different hand orientation changes or to different occlusions. In addition, these methods disclose other drawbacks such as the initialization of the shape which has to be close to the searched object during the detection phase. Therefore, other hand segmentation methods have been proposed in the literature which are based on binarization, elimination of cavities and artifacts. These methods are simple, speedy and showed satisfying detection in the literature especially for images with dark background.

This study also focused on feature extraction methods that are categorized into: (1) feature-based hand geometry, (2) feature-based hand shape and texture and (3) Feature-based hand contour. In fact, feature-based hand geometry treats geometrical measurements of the hand which are based on lengths and widths of fingers, the palm and the hand. These features are robust to rotation and translation, however, they are not robust to scale or some distortions. Moreover, a huge number of measurements is required in order to discriminate features from a person to another for satisfying results, and this may increase computational complexity. On the other hand, feature-based hand shape and texture describe the silhouette

and appearance information. In fact, they are based on PCA (Principal Component Analysis), ICA (Independent Component Analysis) and ART (Axial Radial Transform) features and demonstrate good performances for hand biometric systems [Yoruk 2006b]. Regarding feature-based hand contour, they depict the shape of the hand by localizing landmark points on the hand. These methods are robust to different hand deformations and poses, however, they may cause computational complexity to compute all distances between all landmark points.

Table 3.2 summarizes the different unimodal hand shape and geometry approaches, proposed in the literature. Indeed, concerning hand shape features, promising results have been obtained using shape coding and coherent distance shape contexts, achieving CIR=99.92% and CIR=99.60%, respectively [Briceno 2011, Hu 2012]. However, in these works, experiments were performed on a high number of samples for each subject (10 samples). On the other hand, hand geometry approaches have also been proposed, by calculating the geometrical features of the hand. In fact, the computational complexity of hand geometry systems may be satisfying, due to the simplicity of used techniques. Nevertheless, performances achieved are less promising than hand shape approaches. For example, Yuan et al. [Yuan 2011] extracted 11 geometric features of the hand for persons verification, using a proprietary database which contains 1000 hand images. Experiments achieved a RR=94.2%. However, Guo et al. [Guo 2012] obtained a CIR=96.23% by the extraction of 34 geometrical features of the hand from 6000 hand images. On the other hand, Luque-Baena et al. [Luque-Baena 2013] achieved an EER=4.51% using the IITD hand database and an EER=4.64% using the CASIA hand database. Nevertheless, the authors extracted 403 geometrical features and adopted the Genetic Algorithms methodology in order to select the most pertinent features, which increase the time complexity of this approach.

Therefore, we have the idea, in our proposed work, to combine the hand shape and geometry features as a multi-representation method.

TABLE 3.2: Comparison of some hand shape/geometry biometric systems proposed in the literature.

Reference	Biometric features	Database	Number of images	Characteristics	Performances (%)
[Briceno 2011]	Hand shape	GPDS	1440	Shape coding	CIR ^a =99.92
[Yuan 2011]	Hand geometry	proprietary	1000	11 Geometrical features	RR ^b =94.2
[Hu 2012]	Hand shape	CASIIM	4000	Coherent Distance Shape Contexts	CIR=99.60 EER ^c =0.9
[Guo 2012]	Hand geometry	Proprietary	6000	34 Geometrical features	CIR = 96.23 FAR=1.85
[Luque-Baena 2013]	Hand geometry	-Casia DB -IITD	-600 -822	403 Geometric features	-EER=4.64 -EER=4.51
[Boucetta 2013]	Hand shape	Casia database	500	Hu moments and Legendre moments	RR=97.08

^aCIR : Correct Identification Rate ; ^bRR : Recognition Rate ; ^cEER : Error Equal Rate ;

^dFAR : False Acceptance Rate ; ^eFRR : False Rejection Rate ;

3.3 Palmprint modality

Palmprint is the second physical biometric technology used in our recognition solution so as to characterize a person. In fact, the palmprint represent the texture part of the hand trait. It has the credit of simplicity of collection and user friendliness as well as high recognition accuracy and reliability. However, some problems may occur during acquisition. Actually, palmprint is usually acquired using a touchless device. Since angle and position change during capture process, it is unavoidable to have some geometrical transformations such as rotation, translation, scale changes or illumination variations, which would degrade the performance and the robustness of a palmprint recognition system.

3.3.1 Characteristics of palmprint modality

The palmprint is presented by several characteristics which are classified into three categories according to their scales: principal lines, wrinkles, ridges and minutiae as shown in figure 3.4. It is noted that principal lines and wrinkles may be extracted from a resolution that is less than 100 dpi, whereas the ridges and minutiae may be extracted from a resolution of 400 dpi [Jain 2009]. The advantage of these characteristics is that they are unique and invariable over time.

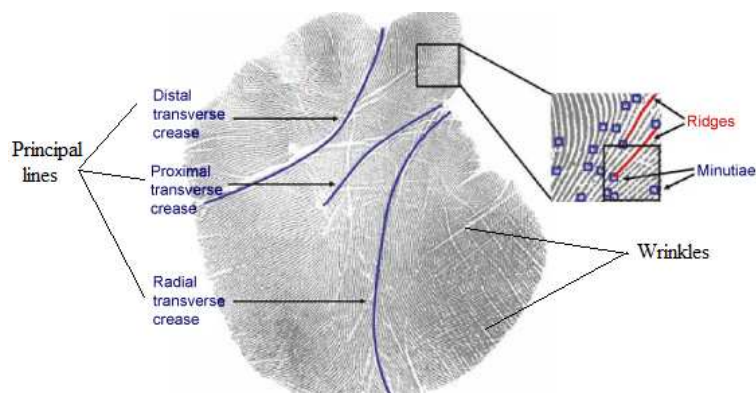


FIGURE 3.4: Characteristics of palmprint modality

Principal lines are the most visible and clear ones which correspond to the flexion creases of the hand. Three prominent creases may be observed in the majority of palms named distal transverse crease, proximal transverse crease and radial

transverse crease [Jain 2009]. Although principal lines are formed with the same manner for all persons, there is a great variability of this line between persons because of the effects of opening and closing of the hand.

The wrinkles of the palm are thinner and more irregular than principal lines which make a random pattern allowing the increase of uniqueness of the palmprint. In fact, the face of the palmprint contains a large number of wrinkles which are stable over time [Dutagaci 2008].

The ridges are only located on the face of the palmprint and the sole of the foot. The ridges of the palm are the thinnest and the most regular lines and they resemble the wrinkles of fingerprints. The shapes of wrinkles differ from one person to another, since they may be considered as a curve or as parallel lines disposed.

The minutiae are the points localized on the continuity change of the ridges. In fact, they are the most commonly used features in fingerprint recognition thanks to their reliability.

3.3.2 Palmprint image acquisition

As hand acquisition, palmprint acquisition may be performed by placing the palm directly on the surface of the device forming a contact palmprint acquisition using for example a commercial scanner, or in front of a simple device like a webcam or a digital camera without direct contact making a contactless or a toucheless palmprint acquisition device. The earlier research studies proposed to integrate pegs to the platform of the acquisition device in order to fix the position of the palm. However, other studies demonstrated later that the use of pegs may produce the deformation of palms and limit the placement of the palm. For these reasons, other devices have been designed without any direct contact nor guiding pegs in order to acquire freely palmprint images. The most widely used and public palmprint datasets are summarized in table 3.3 and described as follows:

- PolyU palmprint database: It was elaborated in the University of Hong Kong Polytechnic, in 2003, and intended for palmprint biometry research. Palmprint images are acquired from 250 volunteers, comprising 195 males and 55 females. The age range is from 20 to 60 years old. The samples were collected in two distinct sessions. In each session, the subject was requested to provide 6 images for every palm. Hence, 24 images of each illumination from 2 palms were taken from each subject. In total, for one illumination, the database includes 6000 images from 500 different palms.
- CASIA palmprint database: It was collected at Chinese Academy of Sciences' Institute of Automation (CASIA), in 2008, containing 5,502 palmprint images acquired from 312 subjects. The palmprint images of both left and right palms are collected for each subject. All the palmprint images are 8 bit gray-level. The device does not restrict poses to limit positions and postures of palms. Subjects are only required to place their palm in front of the device and put it on a uniform colored background. The illumination is distributed evenly and the capture of images is performed utilizing a fixed CMOS camera on the top of the acquisition device.
- IITK palmprint database: It is a public database acquired in Indian Institute of Technology of Kanpur (IITK), in 2009, which contains 549 palmprint images collected from 150 subjects. Each palmprint image has been captured in gray level, in a resolution of 200 dots per inch (dpi) using a low cost flat bed scanner. The user is independent to rotate their hand around $\pm 35^\circ$ symmetric to surface scanner device.

Some examples of acquisition devices are presented in figure 3.5.

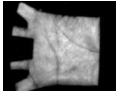


⁵www4.comp.polyu.edu.hk/biometrics/MultispectralPalmprint/MSP.htm

⁶biometrics.idealtest.org/dbDetailForUser.do?id=5



FIGURE 3.5: Examples of palmprint acquisition devices [Zhang 2010].

TABLE 3.3: Some palmprint databases existing in the literature.

	PolyU ⁵	CASIA ⁶	IITK
Year	2003	2008	2009
Number of subjects	250	312	150
Number of samples	24	16	3
Number of images	6000	5502	549
Gray/Color	Gray scale	Gray scale	Gray scale
Resolution	352×288	640×480	200 dpi
Illumination	Red, green, blue, NIR band	Evenly distributed illumination	Non controlled
Devices	CCD Camera	CMOS camera	Scanner
Origin	Chinese	Chinese	Indian
Examples			

3.3.3 Palmprint Region Of Interest (ROI) extraction

The extraction of ROI is a crucial step in palmprint recognition. Several works have been proposed. Tiwari et al. [Tiwari 2013] detected chiefly finger tip and valley coordinates based on local minima and maxima of the hand contour. Afterwards, the valley point V_1 , localized between ring and little fingers, and the valley point V_2 , localized between index and middle fingers, were linked with a line. Subsequently, at these two points V_1 and V_2 , two lines S_1 and S_2 were traced at angles 45° and 60° , respectively. The two midpoints N_1 and N_2 of the segments

$V_1 - S_1$ and $V_2 - S_2$ were represented using the two points T_1 and T_2 which were the intersection points of S_1 and S_2 with the hand contour. Finally, the line segment $T_1 - T_2$ was the side of the square region representing the palmprint ROI, as shown in figure 3.6.

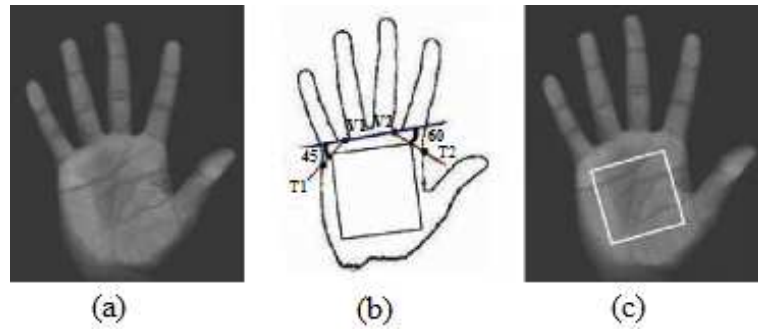


FIGURE 3.6: ROI extraction of Tiwari et al. [Tiwari 2013]: (a) hand image, (b) ROI detection on hand contour, (c) extracted region square of palmprint ROI.

On the other hand, Hammami et al. [Hammami 2014] extracted the palmprint ROI, regardless the distance between the acquisition device and the hand. In fact, it is based on the localization of four valleys from the contour of the hand. These valleys were detected using the radial distance technique. The palmprint ROI extraction was performed as follows:

- The line between the valleys A and B was drawn.
- The mediator $[OE]$ of the segment $[AB]$ was drawn, in which $[OE] = 1/2[AB]$.
- The segment passing through the point E , which is perpendicular to the segment $[OE]$.
- The intersection of this segment with the left and right borders of the hand, forms the two landmarks $F1$ and $F2$. The width of the palm L was determined using the Euclidean distance between $F1$ and $F2$.
- The segment $[OO1]$, which is perpendicular to the segment $[AB]$, was traced with $[OO1] = 1/10L$.

- The segment $[E1E2]$ passing through the point $O1$ and perpendicular to the segment $[OO1]$ was traced, with $[E1E2] = 2/3L$.
- The other three sides $[E1E3]$, $[E3E4]$ and $[E4E2]$ of the palmprint ROI are determined, with the size $2/3L$ for each side.

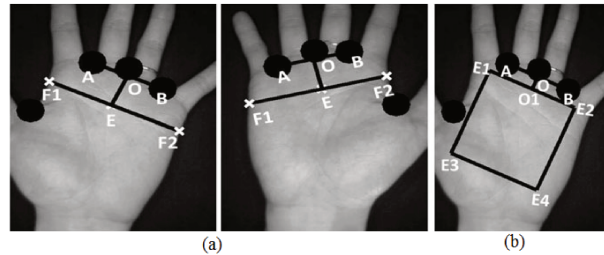


FIGURE 3.7: ROI location of Hammami et al. [Hammami 2014]: (a) determination of the palm width L , (b) ROI detection with $[OO_1]=1/10L$ and $[E_1E_2]=2/3L$.

3.3.4 Palmprint feature extraction

Several palmprint recognition approaches have been proposed in the literature. We distinguish two kinds of approaches: the first one is based on local approaches and the second one is based on global approaches.

3.3.4.1 Local approaches

The palmprint trait was initially characterized by its lines for person recognition. In fact, Zhang and Shu [Shu 1998] used datum points invariant and lines for matching step. Datum points represent the two principal lines extremities which intersect palm boundary with its center. Due to stability of principle lines, their extremities and centers are also stable and invariant. The authors used ink in order to print the palmprint on paper which is scanned to obtain an image of 400×400 . To localize the datum points of principal lines, a directional projection algorithm is used. The matching step is performed using Euclidean distance to compare between a pair of line segments. However, this method presents a limitation in the case of unclear principal lines.

Other researchers [Wu 2006] proposed to use filter to detect line directions (0° , 45° , 90° and 135°) for principal lines and wrinkles extraction. Their structure is represented as a code using Chain Code method and a similarity score is used, in matching step, to compute the proportion of similar points between two palmprint images. Promising performances are achieved on 400 images obtaining 0.84% of EER. Wu et al. suggested previously to reduce time and complexity of the method. Therefore, they developed a method allowing the classification of palmprint images based on principal lines extraction using two steps. The first one consists in using filter to detect line directions for the extraction of initial part of principal lines. The second one consists in applying a recursive process to extract the whole lines depending on the extracted part. Finally, the palmprints are classified into six categories according to the number of principal lines as well as their intersections. This method obtains an accuracy rate of 96.03% using 13800 images acquired from 1380 persons and presents the merit of reducing time and complexity of recognition, since the input palmprint is compared only to those of the same category. However, the extraction of all principal lines is complex and requires too much time.

On the other hand, Sirinivas and Gupta [Srinivas 2009] developed a palmprint verification system based on SURF (Speeded Up Robust Features) descriptors. Initially, the acquisition of hand images was captured using a low cost scanner. Then, a preprocessing step is performed allowing the extraction of palmprint ROI. Regarding the matching step, a sub-image matching process is proposed in order to increase the speed of matching module. Indeed, the extracted palmprint image is decomposed into sub-images and the descriptors of corresponding sub-images are matched. The final number of matched points between the different sub-images is computed and considered for final decision. Experimental results exhibit promising performances for palmprint verification task.

Wu et al. [Wu 2015] proposed a palmprint verification method based on SIFT (Scale Invariant Feature Transform) descriptors. In fact, a model is constructed by approximating non-linearly deformed palm images with piecewise-linear deformed stable regions. Therefore, the KPBG (KeyPoint based Block Growing) method

is proposed. It is based on an iterative M-estimator sample consensus approach using SIFT features. This approach is invented so as to calculate piecewise-linear transformations for approximating the non-linear palmprint deformations, and the stable regions which are conformed to linear transformations are considered using block growing method. Matching scores are measured according to these stable regions for final decision. Experimental results demonstrate the efficiency of this method for palmprint verification field.

Recently, Luo et al. [Luo 2016] have presented a new LBP (Local Binary Pattern) structure descriptor named Local Line Directional Patterns (LLDP) for palmprint recognition. The purpose of this descriptor is to encode the structure of a local neighborhood from the analyzed information of directional line, computed in 12 directions using the MFRAT (Modified Finite Radon Transform) and Gabor filters. Experiments assessed on four databases reveal the robustness of this method and report that this approach outperforms existing LPB descriptors.

3.3.4.2 Global approaches

It is based on extracting global information of palmprints rather than using specifically principal lines or wrinkles features of palmprints.

Zuo et al. [Zuo 2010] proposed a compact representation for multiscale palm line orientation features. Moreover, they investigated a new method named the Sparse Multiscale Competitive Code (SMCC). In fact, this method defined primarily a bank of filters relative to second Gaussian derivatives with different scales and orientations. Afterwards, the sparse coding has been used in order to obtain an efficient estimation of the multiscale orientation area. Finally, the competitive code has been employed for encoding the dominant orientation. Experiments, evaluated using two popular palmprint databases (PolyU and CASIA), indicated that the SMCC method is efficient and offers higher verification rates compared to other existing verification approaches, even using a smaller template size.

Wang et al. [Wang 2012] proposed a global texture method for palmprint recognition based on decomposition using 2D-Gabor Wavelets features. At first, palmprint images are preprocessed and normalized in the position, orientation and illumination. Then, the decomposition of these normalized images into various directional and multiscale subband is performed using Gabor filters and each Gabor subband, in turn, is decomposed into several series of binary images using PCNN (pulse coupled neural network). Entropies of these binary images are computed and considered as features. The identification phase is carried out using SVM (support vector machine) classifier. Experiments reveal good performances and prove the robustness of this method to variation of position, orientation and illumination in comparison to other texture methods.

Guo et al. [Guo 2014] investigated a palmprint recognition method based on HEBD (Horizontally Expanded Blanket Dimension). In fact, blanket dimension is a method allowing the computation of the image surface dimension by employing a blanket technique which captures texture features at different spatial resolutions. The robustness of horizontally, vertically and multi-scale expanded blanket dimensions were compared. Experimental results evaluated on PolyU and CASIA palmprint databases show the efficiency of multi-scale HEBD. Indeed, a high recognition rate is obtained with less execution time.

Recently, Hong et al. [Hong 2016] have developed a palmprint recognition system based on fast Vese-Osher decomposition. This system proposed, firstly, a Gaussian defocus degradation model (GDDM) in order to characterize and process the blurred images of palmprints. Secondly, the structure and texture layers of blurred images are made using the fast Vese-Osher decomposition model. According to this, the structure layer (SL) proves its stability and robustness compared to texture layer. Hence, a new descriptor based on the WHOG-LSP (weighted histogram of oriented gradient for locally selected pattern) is employed in order to extract discriminant features from the SL of blurred images. Finally, the similarity measure is computed using the normalized correlation coefficient. Experiments on PolyU and IITD palmprint databases demonstrate the robustness and effectiveness of this system.

3.3.5 Overview of different palmprint approaches

Recent palmprint recognition approaches are presented and summarized in table 3.4. In fact, several works have been proposed in the literature for palmprint identification and verification. For example, Ghandehari et al. [Ghandehari 2012] suggested a palmprint identification and verification method based on local PHOG (Pyramidal Histogram Oriented Gradients) features, extracted from each scale of the palmprint. This allows the extraction of reliable lines with high contrast and a high accuracy with CIR=99.85% is achieved. It can be seen from table 3.4 that promising performances have been achieved especially for the PolyU palmprint database (CIR=99.36 % [Jing 2013], IR=99.97% [Tiwari 2013], GAR=99.39% [Yue 2014], EER=0.6% [Malik 2011]), containing a high number of palmprint images (7752 images). However, for other databases, namely CASIA palmprint database and IITD hand database, palmprint recognition approaches achieved less performance rates (GAR=96.40% [Yue 2014] for CASIA DB and IR=92% [Luo 2016] for IITD DB). This may be caused depending on the environmental conditions (illumination, images resolution) during acquisition module of the different databases. In fact, the images of CASIA database were acquired using a web camera which makes the quality of images not as good as images of PolyU database. Moreover, CASIA and IITD are contact-free palmprint databases in which there are no palm positions restriction and no pegs limitation, during data acquisition.

TABLE 3.4: Comparison of some palmprint biometric systems proposed in the literature.

Year	Biometric features	Database	Number of images	Characteristics	Performances (%)
[Malik 2011]	Principal lines	PolyU	600	Wavelets + PCA ^g	-FAR=0.06 -FRR=0.06
[Ghandehari 2012]	Principal lines	PolyU	7752	Pyramid Histogram Oriented Gradients ^l	CIR=99.85%
[Chakraborty 2013]	Texture information	Proprietary	500	Dual tree complex wavelet transform (DCTWT) ^g	Accuracy=98.35
[Jing 2013]	Texture information	-PolyU -MSP	-8000 -6000	Two-phase test samples representation (TPTSR) ^l	-EER=0.64 -EER=0.335
[Tiwari 2013]	Texture information	-IITK -CASIA -PolyU	-549 -5238 -7752	Local structure tensor and force field transformation ^l	-IR ^a =100 -IR=99.89 -IR=99.97

Continued Next Page ...

^aIR : Identification Rate ; ^bGAR : Genuine Acceptance Rate;^l : Local approach; ^g : Global approach

Reference	Biometric features	Database	Number of images	Characteristics	Performances (%)
[Yue 2014]	Principal lines	-PolyU -CASIA	-7752 -5237	Consistent orientation pattern (COP) hashing ^l	-GAR ^b =99.39 -GAR=96.40
[Guo 2014]	Texture information	-PolyU -CASIA	-7752 -5502	Multi-scale horizontally expanded blanket dimension (HEBD) ^g	-EER=0.1 -EER=0.5
[Hong 2016]	Texture information	-PolyU -IITD	-7752 -1175	Fast Vese-Osher decomposition model ^g	-EER=0.107 -EER=0.92
[Luo 2016]	Texture information	-PolyU -IITK -Cross-sensor -IITD	-7752 -6000 -12000 -2596	Local line directional patterns (LLDP) ^l	-IR=98.45 -IR=100 -IR=100 -IR=92

3.4 Multimodal hand shape and palmprint biometrics

3.4.1 Challenges of using multimodality

Despite the expected robustness of multimodal biometric systems, they are still limited in terms of their time complexity. In fact, they generally require more time for user registration, which harms some users and reduces their friendliness. Ultimately, the accuracy of a multimodal system depends effectively on the used fusion strategy. Indeed, the recognition rate can be lower than a monomodal system if the adopted technique for combining the different sources is not appropriate.

3.4.2 Design of multimodal biometric systems

During the conception of a multimodal biometric system, it is necessary to take into account some factors that impact the structure of a multimodal biometric system which are described as follows:

- **Cost:** What is the trade-off between additional cost and performance improvement in a biometric system? In fact, cost depends on the number of employed sensors, the time of biometric data acquisition, the requirements of storage, the time of algorithm processing and the degree of convenience perceived by the user.
- **Biometric information sources:** What are the different biometric information sources to be used and what are the most relevant ones for a given application?

- The acquisition and the processing sequence: Should biometric modalities be acquired simultaneously or in series? Moreover, should the acquired information be treated simultaneously or sequentially? Depending on the application scenario, an acquisition and a suitable processing architecture have to be selected.
- Information type: What type of information (features, matching score, decision. . .) have to be fused?
- Fusion method: What fusion scheme should be considered to combine the information presented by multiple biometric sources? The choice of the fusion level is the most important topic in the design of a multimodal system and it has a considerable impact on the performance of the system. The optimal method may be obtained by examining the performance gain at different levels.

It may be noted that the majority of conception choices are based on cost–gain analysis. Typically, there is a trade-off between the additional cost and performance improvement in a multimodal biometric system.

3.4.3 Overview and discussion of hand shape and palmprint fusion approaches

It is really difficult to establish a comparison between recently published different methods. In fact, depending on each specific environment and application, various factors should be taken into account in order to choose the most appropriate one. Thus, principal characteristics of the recent multimodal approaches of hand shape and palmprint modalities, appeared in different conferences and journals, are summarized in table 3.5.

As it can be seen from table 3.5, the most widely used fusion levels in multimodal systems are feature level and score level. In fact, multi-biometric methods have been proposed, fusing hand geometry and palmprint modalities [Prasad 2009,

Wang 2009]. The fusion was performed at feature level and on $RR \approx 97\%$ was achieved. On the other hand, Liliana et al. [Liliana 2012] fused hand shape and palmprint modalities at feature level. Nevertheless, a rather weak performance was achieved ($IR=89\%$) for only 200 hand images. The multi-instance fusion of left and right hand geometry or left and right palmprints has also been presented at feature level [Asish 2015, Leng 2015]. These works offer promising performances by achieving $CIR=99.5\%$ and $IR=99.7\%$ using, respectively, 603 and 2020 hand images [Asish 2015, Leng 2015].

With respect to the fusion at score level, a multi-representation fusion method has been proposed by Chen [Chen 2008], fusing two descriptors namely SIFT descriptors and Symbolic Aggregate approxImation (SAX) descriptors extracted from palmprint images. Experiments obtained an $EER=0.37\%$ using 7752 palmprint images. On the other hand, Kang et al. [Kang 2014] proposed to fuse Fourier descriptors and finger area function in order to describe the hand geometry. Experiments using 1914 hand images revealed an $EER=3.69\%$. However, Sharma et al. [Sharma 2015] combined hand shape and geometry features at matching score level. The evaluation of this method is performed using 500 and 1200 hand image, obtaining $EER=0.31\%$ and $EER=0.52\%$, respectively. In the case of multi-instance fusion [Xu 2015], left and right palmprints are fused. The best performance rate achieved an $IR=99.64\%$ using palmCode features with 3740 palmprint images of PolyU palmprint database. Moreover, Orthogonal Line Ordinal Features (OLOF) and SIFT descriptors were fused and an $IR=99.57\%$ was obtained using IITD hand database [Xu 2015]. Ferrer et al. [Ferrer 2011] fused 15 geometrical features from hand geometry and Gaussian filter from palmprint modality at score level. Different databases were used in experiments, namely GPDS, IITD and a proprietary database. In this respect, results showed promising performances obtaining an $EER < 1\%$.

The fusion at decision level is rarely used (as seen in table 3.5) since it treats less information compared to other fusion levels. However, good performances may be achieved at this level. For example, Asish et al. [Asish 2015] achieved promising

performances (FAR=0.625%) by fusing left and right hands but using only 603 hand images.

3.5 Conclusion

In this chapter, we have presented a survey of hand shape and palmprint modalities. Firstly, the different existing databases of hand shape and palmprint modalities are summarized. Then, an overview of hand shape and palmprint approaches are discussed and compared. On the other hand, the multimodality challenges are described and the different hand shape and palmprint fusion approaches are discussed.

The second part of this manuscript will cope with the different contributions proposed in this thesis.

TABLE 3.5: Comparison of some fusion approaches of hand shape and palmprint modalities.

Reference	Modality	Multi-type	Database	Number of images	Features	Fusion level	Performances (%)
[Chen 2008]	Palmprint	Multi-representation	PolyU	7752	SIFT + SAX	Score	EER=0.37
[Adan 2008]	Left/Right hand's contours	Multi-instance	Proprietary	5640	Geometric features	Feature	-FAR=1.3 -FRR=1.3 -IR=97.6
[Prasad 2009]	Hand geometry + Palmprint	Multi-biometrics	Proprietary	240	-Geometric features -Wavelet features	Feature	RR=97.5
[Wang 2009]	Hand geometry + Palmprint	Multi-biometrics	Proprietary	1560	-Contour features -Wavelet features	Features	-FAR=0.35 -FRR=5.7
[Ferrer 2011]	Hand geometry + Palmprint	Multi-biometrics	-GPDS -IITD -Proprietary	-1500 -2340 -1000	-15 geometric features -Gaussian filter	Score	-EER=0.01 -EER=0.79 -EER=0.17
[Liliana 2012]	Hand shape + Palmprint	Multi-biometrics	Proprietary	200	-Chain code -Std of each block of ROI	Feature	-IR=89
[Kang 2014]	Four fingers geometry	Multi-representation	Bosphorus	1914	-Fourier descriptors -Finger area functions	Score	EER=3.69

Continued Next Page ...

Reference	Modality	Multi-type	Database	Number of images	Features	Fusion level	Performances (%)
[Asish 2015]	Hand geometry Left/Right	Multi-instance	Bosphorus	603	26 geometrical features	-Features -Decision	-CIR=99.5 -FAR=0.625
[Sharma 2015]	Hand shape/geometry	Multi-representation	-Proprietary	-500	-Distance and orientation map	Score	-EER=0.31
			-IITD	-1200	-7 geometrical features		-EER=0.52
[Leng 2015]	Palmprint Left/Right	Multi-instance	Proprietary	2020	Two-dimensional discrete cosine transform	Feature	IR=99.7
[Xu 2015]	Palmprint Left/Right	Multi-instance	-IITD		-PalmCode		-IR=97.1
			-		-OLOF+SIFT		-IR=99.57
			-PolyU	-3290	-PalmCode	Score	-IR=99.64
			-	-3740	-Ordinal code		-IR=98.84
			-		-SIFT descriptors		-IR=94.64

Part II

CONTRIBUTIONS

Chapter 4

Verification approach based hand shape modality

Contents

4.1	Introduction	75
4.2	Methods and techniques	76
4.2.1	Scale Invariant Feature Transform (SIFT)	76
4.2.1.1	Scale space detection	76
4.2.1.2	Key point localization	77
4.2.1.3	Key point description	77
4.2.2	Gabor filters	78
4.3	The proposed Sift Matching Refinement based Hand Shape Verification (SMRHSV)	79
4.3.1	Preprocessing module	79
4.3.1.1	Keypoints detection	79
4.3.1.2	Modified SIFT extraction	82
4.3.2	The matching refinement	82
4.3.2.1	First level: matching based-region refinement	83
4.3.2.2	Second level: matching based-BHD refinement	84
4.4	Experimental evaluation	85
4.4.1	Experimental corpus	86
4.4.2	Verification results	86
4.4.3	Execution time performance	88
4.5	Discussion and comparison	88

4.6 Conclusion	89
---------------------------------	-----------

4.1 Introduction

The current chapter presents the proposed hand verification approach. Figure 5.1 summarizes the various approach types adopted in our approach, for different modules (represented by ✓) vs. other existing types.

This chapter introduces primarily the different methods and techniques used in this approach. Thereafter, it details the proposed approach based SIFT matching refinement algorithm for hand shape verification. Then, the experimental evaluation is revealed. Finally, the achieved results are discussed and compared to other popular hand shape approaches.

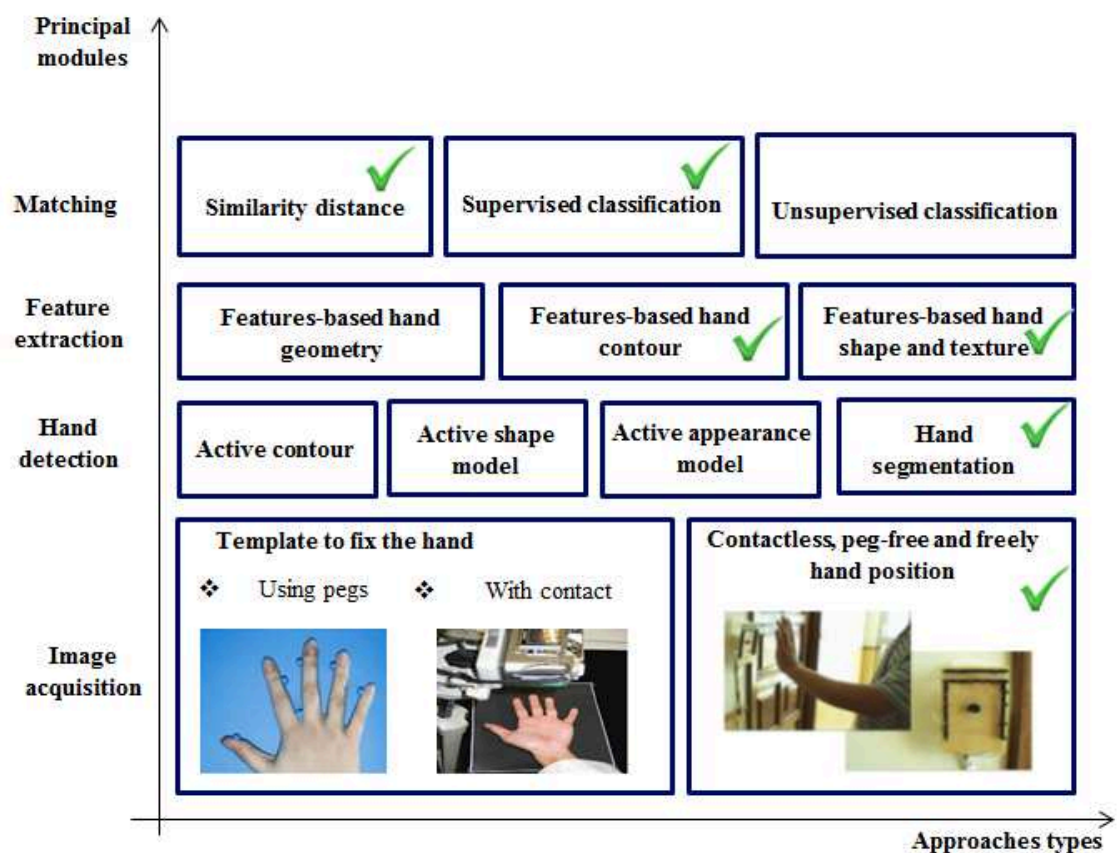


FIGURE 4.1: The position of the proposed hand shape verification method vs. different approaches existing in the literature.

4.2 Methods and techniques

This section presents the different techniques and methods used in the proposed hand shape verification approach, including the Scale Invariant Feature Transform (SIFT) and Gabor filters.

4.2.1 Scale Invariant Feature Transform (SIFT)

Scale Invariant Feature Transform (SIFT) is a feature extraction proposed by Lowe [Lowe 1999] in 1999 to detect and describe keypoints in an image. It consists not only of detecting but also characterizing (by values) to further recognize (match) these keypoints in other images of the same scene. This algorithm has a great success in different applications of computer vision field as well as other areas. The main idea of SIFT algorithm is to find features which are invariant to several transformations like rotation, scale changes, illumination and affine distortion. SIFT algorithm may be explained in the following steps:

4.2.1.1 Scale space detection

After preprocessing step, the obtained hand image is convolving with a list of Gaussian kernels in different scales to construct the Gaussian scale space through:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (4.1)$$

Where $L(x, y, \sigma)$ represents the Gaussian kernel in scale σ , $I(x, y)$ is the enhanced hand image and $G(x, y, \sigma)$ is a variable-scale function defined as:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2 + y^2)/2\sigma^2} \quad (4.2)$$

4.2.1.2 Key point localization

Key point is localized using the Gaussian scale transform which is defined as the difference of Gaussians (DoG). It is achieved by the subtraction of two neighbor scales separated by the scale factor k [Lowe 2004], as expressed in (4.3).

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma) \end{aligned} \quad (4.3)$$

Each sample point is compared to its eight neighbors in the current scale image and nine neighbors in the previous and next scales. If it is maxima or minima of DoG, this point is considered as key point candidate in that scale. The key point candidates are, thus, filtered using a threshold to reject unstable ones that are sensitive to noise. Therefore, only key points invariant to affine transformations and insensitive to noise are given, in this step.

4.2.1.3 Key point description

The descriptor of a detected keypoint of a region of interest represents the orientation histogram of gradients in the region (figure 4.2).

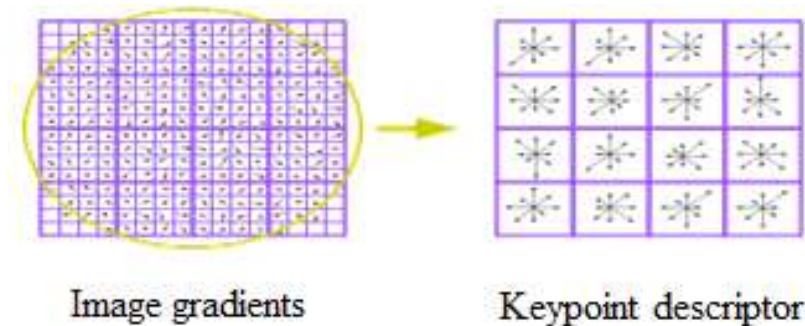


FIGURE 4.2: Keypoint description in different orientations (8 directions)

The key point descriptor is made according to the gradient magnitude $m(x,y)$ and orientation $\theta(x,y)$ of each key point in a region. They are defined as:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \quad (4.4)$$

$$\theta(x,y) = \tan^{-1}\left(\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}\right) \quad (4.5)$$

The orientation of one key point is gotten according to the orientation histogram created with 36 orientations. The peak orientation is considered as the main orientation of this key point. Axis has to be rotated according to the orientation of the key point, in order to obtain rotation invariance. Then, the key point is described with 16 sub-blocks (4×4) around and the gradient orientation histogram is computed for each sub-block with eight orientations, which form the $4 \times 4 \times 8 = 128$ values feature vector for each key point [Lowe 2004].

4.2.2 Gabor filters

Gabor filters have been well emerged in pattern analysis field [Meshgini 2013, Shen 2007]. In fact, Gabor filter is a linear filter employed for edge detection. Orientation and frequency representations of Gabor filters, which are similar to those of the human visual system, have been considered notably suitable for texture representation and distinction. A filter bank which consists of Gabor filters with different scales and orientations is created. The advantage of Gabor filters consists of their invariance to rotation, translation, scale and illumination. 2-D Gabor filter is defined, in the spatial domain, as a Gaussian kernel function modulated by a sinusoidal plane wave, as follows [Haghighat 2013]:

$$g(x,y) = \frac{f^2}{\pi\gamma\eta} \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \exp\left(j2\pi f x' + \phi\right) \quad (4.6)$$

$$x' = x \cos \theta + y \sin \theta$$

$$y' = -x \sin \theta + y \cos \theta$$

where f and θ represent the frequency and the orientation, respectively. ϕ is the phase offset, σ represents the standard deviation of the Gaussian envelope and γ is the ratio of the spatial aspect that indicates the elliptical effect of the Gabor function support.

4.3 The proposed Sift Matching Refinement based Hand Shape Verification (SMRHSV)

In this section, the proposed verification approach based hand shape biometric modality is described. The first problematic in hand recognition is to search robust similarities between hands, even with possible deformations of the hand image, such as lighting and scale changes or geometrical transformations like rotation and translation, etc. The recent methods consist of describing efficiently each image by one or several descriptors. Hence, the aim is to construct a descriptor that should be invariant according to desired criteria (rotation, scale, etc.) for hand shape recognition (based on hand contour). To achieve a robust and accurate solution, the proposed hand shape verification method is composed of four principal modules: (1) the preprocessing module, (2) the feature extraction and matching module, (3) the matching refinement module and (4) the decision module, as illustrated in figure 4.3.

4.3.1 Preprocessing module

4.3.1.1 Keypoints detection

In this section, our first contribution is given. Differently to existing methods, a solution is defined to detect a set of hand shape keypoints. Indeed, the shape of the hand is mainly represented by the contour of the hand. For this reason, the first step is to find precisely the contour of the hand trait.

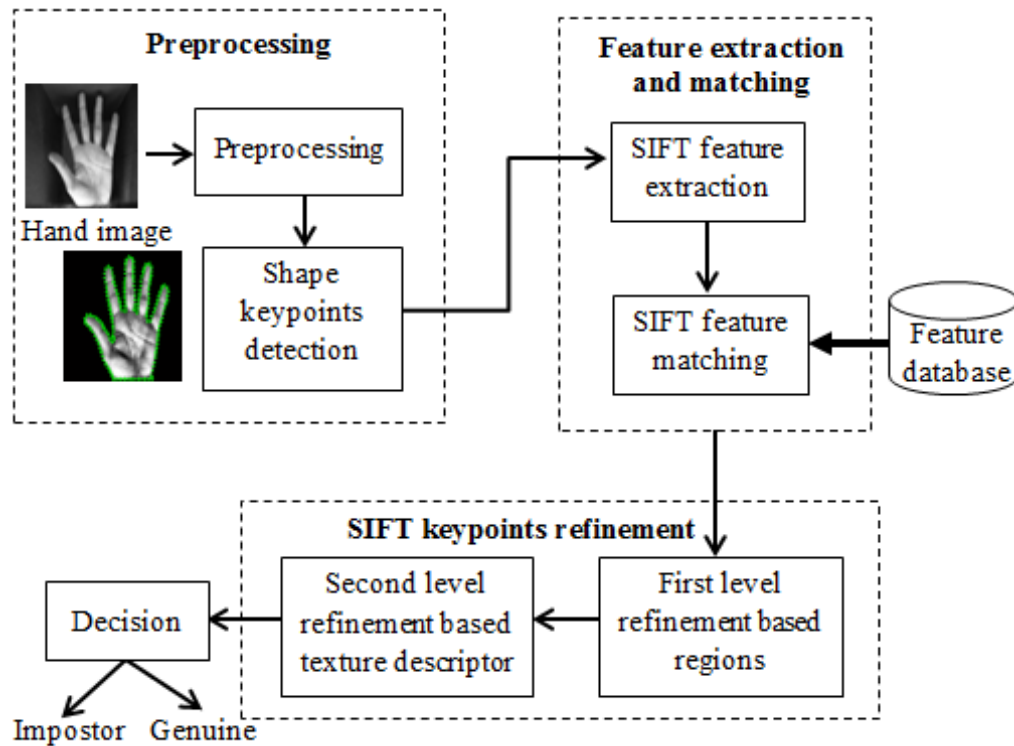


FIGURE 4.3: The proposed hand shape verification method.

Some preprocessing steps were adopted to the hand images before performing key-point detection, namely, segmentation of the hand, fingertips and valleys detection, completion of the wrist and hand contour detection.

A. Segmentation of the hand

Image acquisition devices using digital camera or scanner produce mainly a two-class image including hand texture (or appearance) in the foreground of the image and a darker background. At first, the two-class Kmeans clustering technique is used. In fact, the k-means method is a classification technique which divides a set of data into k homogeneous classes. Subsequently, it may provide an effective solution to image segmentation problem. Then, the morphological operators are employed in order to fill in holes and eliminate isolated debris [Soille 2003]. Finally, size filtering is applied on the hand image connected components in order to eliminate spurious components presented in the background. These steps extract and separate satisfactorily the hand from the background as shown in figure 4.4(b). The output of the hand segmentation is a binary image which corresponds to the hand silhouette.

B. Wrist removal

The hand contact-free acquisition may cause several deformations in the wrist region due to the position variations or clothing occlusion. These deformations can make hand contours irregular in each session which may negatively affect the authentication performances. Hence, for every hand image, we aim to eliminate the unneeded part of wrist (as shown in figure 4.4).

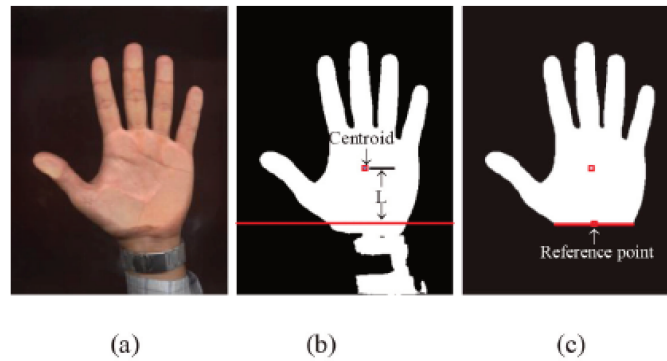


FIGURE 4.4: (a) Original hand image (b) Binary hand image (c) Wrist removal using reference point and centroid.

C. Finger tips and valleys localization

Finger tips and valleys extracted using an efficient method which is based on the computation of radial distances while respecting the reference point that is localized around the wrist region. Indeed, this point may be formed by the first intersection point of the wrist line and the major axis. The five maxima (finger tips) and the four minima (finger valleys) are generated according to the sequence of radial distances as represented in figure 4.5.

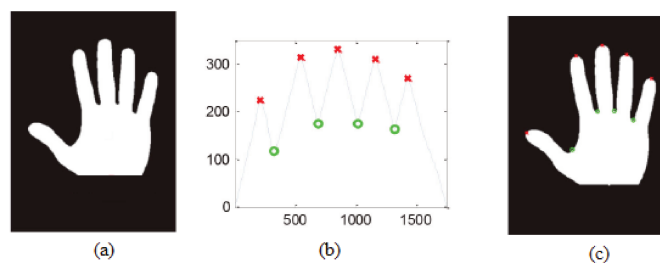


FIGURE 4.5: (a) Binary image (b) Radial distance function (c) Localization of five fingertips and four finger valleys.

4.3.1.2 Modified SIFT extraction

In this section, our proposed SIFT feature extraction of the hand is presented. Our aim is to describe the shape of the hand. In fact, the shape is defined as the external boundary of the hand object. However, key points detected on hand images, using original SIFT algorithm, do not form the shape of the hand since key points are localized inside the hand image as demonstrated in figure 4.6. Therefore, in our work, we propose to localize points from the contour of the hand. Thus, first, the longest contour of the binarized hand image is extracted. Then, redundant points in the contour are removed. The shape is, thus, sampled with roughly uniform spacing on the external boundary of the hand object. Several number of points were experimented in order to select the best set of points which discriminate efficiently the hand shape from one person to another. Furthermore, SIFT descriptors are computed around this set of points of the hand shape.

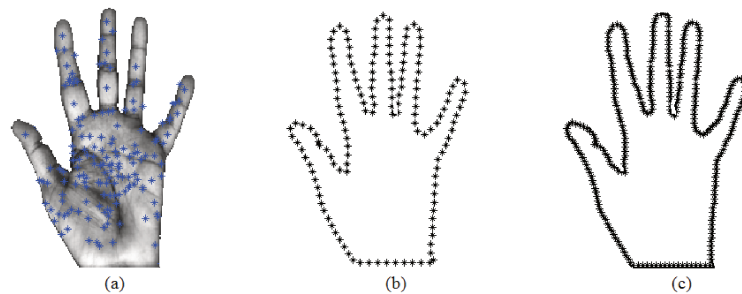


FIGURE 4.6: Localized keypoints:(a) using original SIFT detector, (b)using proposed 150 points, (c) using proposed 300 points.

4.3.2 The matching refinement

According to the computation of SIFT descriptors from localized hand shape keypoints, the SIFT feature matching is given. Indeed, the Euclidean distance is adopted so as to match two hand images descriptors. As a matter of fact, a pair of keypoints are considered as matched if

$$d_{ni} < t \min(d_{nj}), j = 1, 2, \dots, N; j \neq i \quad (4.7)$$

where d_{ni} and d_{nj} represent the Euclidean distances computed between the keypoints of two descriptors p_n, q_i and p_n, q_j and t represents a threshold chosen as 0.6 according to previous work [Morales 2011]. Figure 4.7 presents an example of matched keypoints between two hand images.

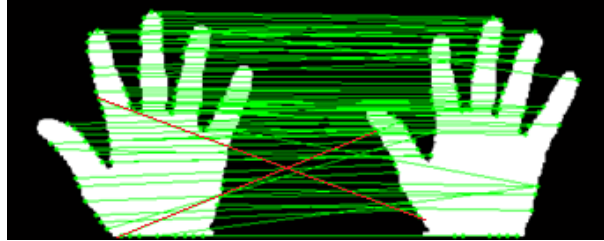


FIGURE 4.7: False matches between two keypoints (red matches) localized in different regions.

Nevertheless, several keypoints are falsely matched (as red lines seen in figure 4.7). In fact, the decision of this unimodal biometric system is made according to the number of matched keypoints. Thus, false acceptances may be caused due to false matches. For this reason, a matching refinement process is proposed in order to refine as much as possible the number of matched keypoints between two hand images. This process is composed of two levels: region based refinement and Boundary Hand Descriptor (BHD) based refinement.

4.3.2.1 First level: matching based-region refinement

It consists of a refinement according to the regions of matched keypoints. In fact, multiple pairs of keypoints are falsely matched. For example, a keypoint localized in the index finger is matched to a keypoint localized in the palm region. These matches are regarded as false ones and they have to be removed.

To cope with these problems, a matching refinement process is proposed in order to refine as much as possible false keypoint matches detected. Therefore, as a first step, the hand area is decomposed into six regions, including palm region, thumb finger, index finger, middle finger, ring finger and little finger as shown in figure 4.8 (b). The decomposition was performed by detecting tips and valleys points of the hand image, as described in section 4.3.1.1. Moreover, three auxiliary points of

thumb, index and little fingers should be detected to separate correctly fingers and palm regions as shown in figure 4.8 (a). The matching between keypoints localized in different regions (palm region is matched with index finger region) have to be removed. Hence, the number of the matched keypoints would be reduced and refined compared to the initial feature matching algorithm.

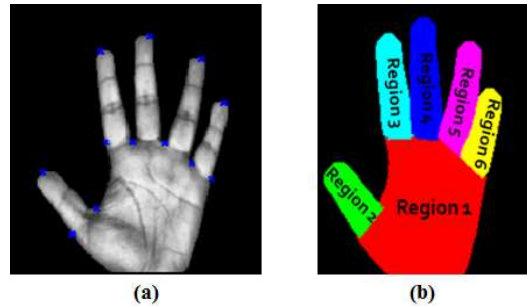


FIGURE 4.8: (a) Detected hand landmark points (b) Hand divided into six regions (the palm and the five fingers).

4.3.2.2 Second level: matching based-BHD refinement

After the first level of matching refinement, some mis-matched keypoints still exist. Indeed, even several keypoints belong to the same region, they may not have the same texture characteristics. Therefore, a second level is required to refine matched keypoints having different textures. In fact, texture features are extracted from each matched keypoint using a patch image forming the Boundary Hand Descriptor (BHD). The BHD of a matched keypoint $k(x, y)$ at (x, y) is defined as the local hand boundary feature extracted from a square boundary image patch centered at (x, y) as shown in figure 4.9. To represent the texture of this patch, forty Gabor filters with five scales and eight orientations are employed [Haghighat 2013]. To compare two feature vectors corresponding to two matched keypoints, a similarity measure is computed. If this measure is lower than a certain threshold δ , then these two points are considered as mis-matched and have to be removed.

The total number of correctly matched SIFT keypoints is regarded as the final score in order to make a final decision of our SMRHSV system. The process of this system is detailed in algorithm 1.

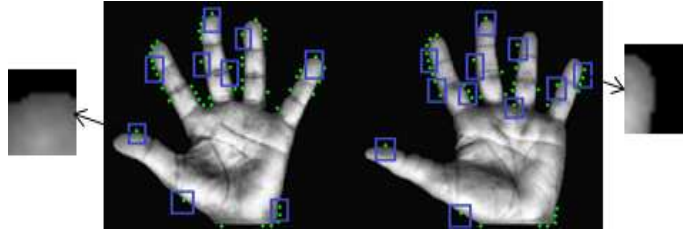


FIGURE 4.9: Hand boundary patch definition.

Algorithm 1: Keypoint matching refinement process for hand shape recognition**Input:**

1. Two matched hand images $I_1(x_1, y_1)$, $I_2(x_2, y_2)$
2. Matched boundary keypoint set: $K = \{(n, m)^l | l = \{1, 2, \dots, N\}\}$ where $(n, m)^l$ represents the l^{th} pair of matched keypoints and N is the pairs number of matched keypoints

Output:

K_1 : New set of matched keypoints after refinement

N_1 : Number of refined matched keypoints

1. Initialization: $S_{FM} = \emptyset$ (FM: False Matched points)
2. Decompose input hands I_1 and I_2 into six regions R_j , $j = \{1, \dots, 6\}$
3. **for** $t = 1$ to N **do**
 - if** $keypoint_n$ and $keypoint_m \notin$ the same region R_j **then**
 - (a) Remove these two matched keypoints
 - (b) $S_{FM} = S_{FM} + (n, m)^t$
 - (c) $N = N - 1$
4. **for** $s = 1$ to N **do**
 - (1) Compute BHD_n , BHD_m for keypoints n , m with $(n, m)^t \in S_{FM}$ using eq.4.6
 - (2) Match BHD_n , BHD_m and compute the distance d
 - (3) **if** $d > \delta$ **then**
 - (a) Remove $(n, m)^t$
 - (b) $S_{FM} = S_{FM} + (n, m)^t$
 - (c) $N = N - 1$
5. $K_1 = K - S_{FM}$
6. $N_1 = N$

4.4 Experimental evaluation

In this section, the experiments and results of the proposed method is described and analyzed.

4.4.1 Experimental corpus

The IITD Toucheless hand database, described in chapter 3, is used for experiments. In fact, 1150 left hand images captured from 230 subjects are considered. For persons verification process, the first three images are adopted for training phase and the rest are adopted for testing phase. Some examples of hand images are presented in figure 4.10.



FIGURE 4.10: Examples of IITD hand database.

4.4.2 Verification results

The verification mode consists of verifying the identity of the person who claims to be using his physiological features. In order to assess performances of the proposed biometric system, various rates should be computed including the false rejection rate (FRR), the false acceptance rate (FAR) and the recognition (or verification) rate (RR). The equal error rate (EER) is presented when FRR and FAR are equal. In this work, hand shape modality is adopted in order to verify the identity of the person. Unlike other biometric approaches that detect SIFT keypoints for further SIFT description, our proposed verification approach localize 300 points on the contour of the hand to extract, then, SIFT descriptors corresponding to the localized keypoints. Compared to standard SIFT algorithm, the proposed approach presents a lower EER = 5.45% (compared to EER = 5.86% for standard SIFT algorithm), as shown in table 4.1.

A matching refinement process is also proposed in two levels based on the matching-based region refinement and the matching-based BHD refinement. The proposed SMRHSV method reveals better performances with EER = 3.85% compared to Luque- Baena et al's system which achieves EER = 4.51% as seen in table 4.2.

TABLE 4.1: Performance verification rates (%)

Methods	EER (%)
Standard SIFT algorithm	5.86
SIFT algorithm without refinement, using proposed keypoints	5.45
Proposed matching method based-refinement	3.85

TABLE 4.2: Comparison of performances results of our hand shape verification approach vs. other popular approaches

References	Methods	EER (%)
Fouquier et al., 2007 [Fouquier 2007]	Geometry	4.24
Adan et al., 2008 [Adan 2008]	NRS	4.40
Ferrer et al., 2011 [Ferrer 2011]	Geometry	5.28
Luque-Baena et al., 2013 [Luque-Baena 2013]	Geometry	4.51
Our approach	SIFT based matching refinement	3.85

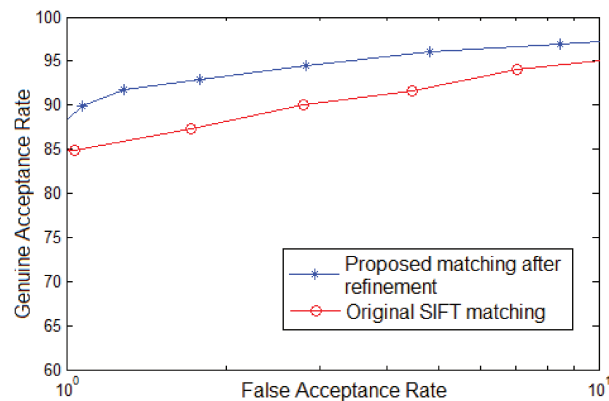


FIGURE 4.11: ROC curve performances of the proposed approach Vs. original SIFT algorithm.

With regards to the comparison with other results reported using original SIFT algorithm, the proposed approach is more efficient for contactless hand modality recognition. In fact, since the matching refinement process supplies more discriminability to keypoints compared to original SIFT descriptors, the reliability of matching refinement process is higher.

As reported in table 4.2, the performance verification rates demonstrate that

TABLE 4.3: Execution time

Steps	Average execution time (ms)
Preprocessing	750
SIFT Feature extraction	451
SIFT Feature matching	75
Region based-refinement	44
Texture based-refinement	412
Total	1732

the proposed approach is more efficient by reaching a recognition rate (RR) of 96.15% and an EER of 3.85% compared to the original SIFT matching method (RR=93.98%). Our approach is also compared to other existing systems in terms of EER. Indeed, as shown in Table 4.2, Ferrer et al. [Ferrer 2011] have extracted geometrical features of the hand including 400 finger widths and obtained 5.28% of EER using left hand images of IITD hand database. On the other hand, Luque-Baena et al. [Luque-Baena 2013] have achieved 4.51% of EER by extracting 50 geometrical features from the hands of the same database.

4.4.3 Execution time performance

The proposed method is implemented using Matlab 2014a on a computer with 2.5 GHz, Intel core i3 CPU and 4GB RAM. Table 4.3 listed the execution time relative to each step (regarding SIFT feature extraction and matching, the toolkit developed by Vedaldi [Vedaldi] is adopted). Our verification method requires 1.7s of the total execution time without code optimization.

4.5 Discussion and comparison

As mentioned in chapter 3, pegs were used in some systems in order to specify the placement of the hand [Jain 1999a, Sanchez-Reillo 2000]. Nevertheless, this

technology may deform the shape of the hand and decrease users' convenience for the acquisition device. Therefore, other researchers suggested for users to touch the same glass during acquisition which cause some artifacts because of the pressure of users on the glass plate. However, some users do not accept to put their fingers on the same glass plate for hygienic reasons.

Accordingly, in our work, we have taken these constraints into consideration by capturing hand freely without direct contact and without any restriction on the position and the orientation of the hand, neither the lighting changes. Furthermore, contrary to existing works in literature which use geometrical characteristics of the hand as input to their recognition system, the proposed method finds its uniqueness and originality to exploit points from the contour of the hand. These points are inputted to the SIFT descriptor method for features extraction, unlike other works [Ghoualmi 2015] which considered SIFT detector to detect keypoints from an image. Moreover, in contrast to other existing methods that generate the final decision about the identity of the person by computing the number of matched SIFT keypoints, the proposed method suggests a refinement stage for SIFT matching algorithm in order to refine and remove as much as possible false matched points between two hand images.

4.6 Conclusion

The proposed hand shape verification method is described. Two contributions are presented in the hand shape recognition field. The first one is based on the detection of keypoints localized on the contour of the hand for further SIFT description. The second one is based on a two-stage matching refinement process.

The next chapter will put forward the proposed palmprint identification method.

Chapter 5

Identification approach based palmprint modality

Contents

5.1	Introduction	91
5.2	Methods and techniques	91
5.2.1	Sparse representation (SR) concept	91
5.2.1.1	Overcomplete dictionary	93
5.2.1.2	Sparse representation	94
5.2.2	Support Vector Machines (SVM)	95
5.3	Proposed identification approach based palmprint modality	96
5.3.1	Palmprint ROI extraction	96
5.3.2	Feature extraction	97
5.3.3	Palmprint identification	99
5.4	Experimental evaluation	100
5.4.1	Proposed prototype	100
5.4.2	Experimental results	101
5.4.3	Execution time performance	105
5.5	Conclusion	105

5.1 Introduction

Palmprint is the second physical biometric technology used in our recognition solution in order to characterize a person. In fact, the palmprint represents the texture part of the hand trait. It has the merit of simplicity of collection and user friendliness as well as high recognition accuracy and reliability. However, some problems may occur during acquisition. Indeed, palmprint is usually acquired using a touchless device. Because of the angle and position changes during capture process, it is unavoidable to have some geometrical transformations such as rotation, translation, scale changes or illumination variations, which would degrade the performance and the robustness of a palmprint recognition system. To deal with these problems, SIFT descriptors are extracted from palmprint images due to their advantages of rotation, translation and scale changes invariance. SIFT features are combined linearly using sparse representation method.

In this chapter, we firstly present a preview of the different used techniques in section 5.2. Then, our palmprint identification method is detailed in section 5.3. Finally, experiments and results are reported, in section 5.4, allowing the validation of the proposed method performances. Figure 5.1 summarizes the various approach types adopted in our palmprint identification approach for different modules (represented by ✓) vs. other existing types.

5.2 Methods and techniques

5.2.1 Sparse representation (SR) concept

Recently, sparse representation (SR) approach has proven its effectiveness in solving different tasks in computer vision field. In fact, SR is able to reveal semantic information of the image (or signal). The principle idea of SR consists of representing a signal $y \in \mathbb{R}^m$ as a linear combination of a small number of elements,

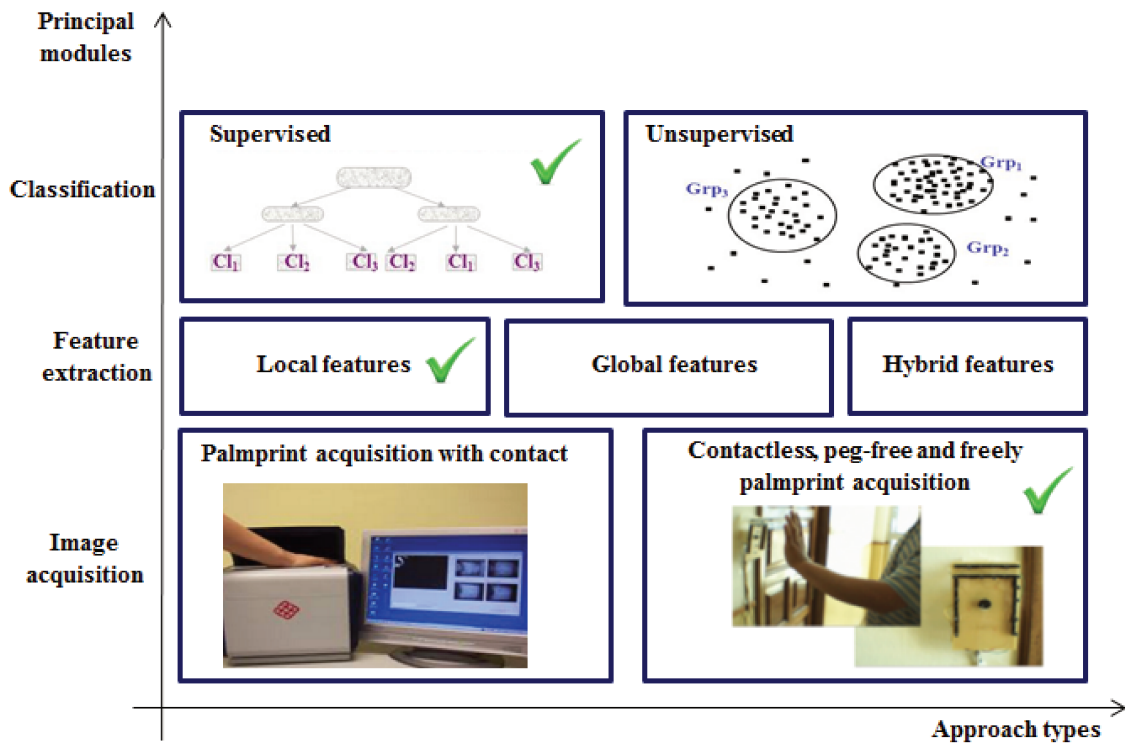


FIGURE 5.1: The position of the proposed palmprint identification method vs. approach types.

named *atoms*, that are selected from an *overcomplete dictionary*. This principle is illustrated in figure 5.2.

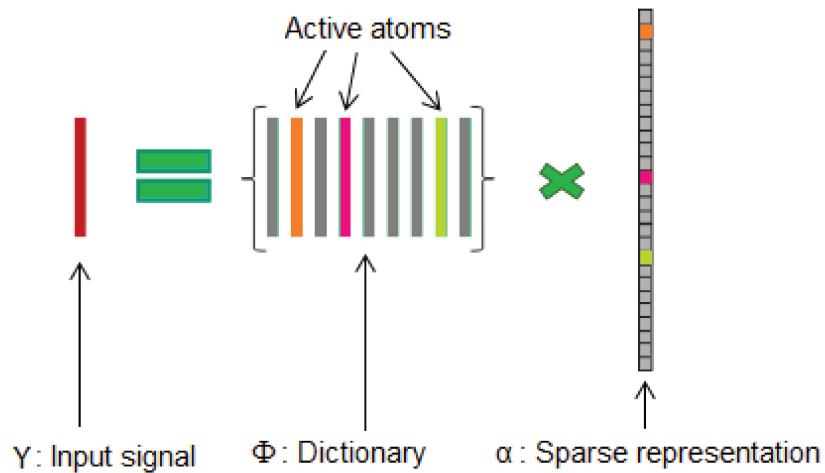


FIGURE 5.2: Illustration of sparse representation principle

5.2.1.1 Overcomplete dictionary

A dictionary $\Phi \in \mathbb{R}^{K \times M}$ is a set of elementary signals named atoms, given by:

$$\Phi = \{\phi_k\}_{k \in \Psi}, \Psi = \{1, \dots, K\} \quad (5.1)$$

where the atoms ϕ_k are discrete signals with length M . In fact, a dictionary may be categorized into overcomplete, complete or undercomplete, in terms of whether the dictionary spans the space of signal or not. The "complete dictionary" is defined if the atoms span entirely the signal space making a basis. On the other hand, if the number of atoms is higher than the signal space dimension ($K \gg M$) and a basis may be formed by a subset in the dictionary, it is called an "overcomplete dictionary". In the other case, if the number of atoms is less than the signal space dimension ($K < M$), the dictionary is called "undercomplete dictionary". Indeed, overcomplete dictionaries are built by combining bases or using additional basis functions to the complete dictionary. Overcomplete dictionaries have a good ability to provide sparse representation of signals [Aharon 2006], they have, thus, become a significant tool regarding signal processing area.

Thus, an input signal $y \in \mathbb{R}^K$ may be represented as a linear combination of the elements selected from a dictionary Φ by satisfying:

$$y \approx \Phi \alpha = \sum_{k=1}^K \alpha_k \Phi_{\phi k} \quad (5.2)$$

where α_k represents the coefficients of the signal and $\phi \in \Psi$ represents the index relative to the atom Φ .

Nevertheless, this representation is not unique for overcomplete dictionaries, which allows us to search the optimal combination solution for the required problem. The aim, in the case of the sparse representation problem, is to search the most robust representation permitting the reconstruction of the signal using the minimum reconstruction error.

5.2.1.2 Sparse representation

The sparse representation problem may be expressed, in function of a signal $y \in \mathbb{R}^K$, a dictionary $\Phi \in \mathbb{R}^{m \times k}$ containing k elements and a vector $\alpha \in \mathbb{R}^k$ of the representation coefficients of the input signal y , as follows:

$$\min_{\alpha} \|\alpha\|_0 \text{ s.t. } \|y - \Phi\alpha\|_2 \leq e \quad (5.3)$$

where $\|\alpha\|_0$ represents the l_0 -norm of the vector α (i.e. counts the number of nonzero elements in α) and e represents a permitted error reconstruction. Although solving l_0 -norm is usually difficult (NP-hard problem), several algorithms look for obtaining an approximate solution to this problem. In [Chen 2001], Chen *et al.* suggested solving the sparse representation problem for overcomplete dictionaries by utilizing a convex optimization method that searches to minimize the l_1 -norm as:

$$\min_{\alpha} \|\alpha\|_1 \text{ s.t. } \|y - \Phi\alpha\|_2 \leq e \quad (5.4)$$

Nevertheless, convex optimization methods present the limitation to be expensive in terms of computation in the case of solving of a very large system [Hameed 2012]. To solve, efficiently, the problem of l_1 -minimization, Least Absolute Shrinkage and Selection Operator (LASSO) method is invented by Tibshirani [Tibshirani 1994] in which the aim is to find an estimation of α allowing the minimization of the least square error subject to a l_1 -norm, expressed as follows:

$$\min_{\alpha} \frac{1}{2} \|y - \Phi\alpha\|_2^2 + \lambda \|\alpha\|_1 \quad (5.5)$$

where the parameter $\lambda > 0$ is intended to control the compromise between the sparsity of α and the least square error. This optimization problem converges to solve the l_1 -minimisation problem when λ tends to zero.

In spite of the simplification of l_0 -norm optimization problem, the difficulty of resolution still exists. Indeed, there are two possible issues: (i) finding the most compact sparse representation for a given dictionary; (ii) finding the most

appropriate dictionary corresponding to the class of signal to be processed. To overcome the first issue, several sparse approximation methods have been developed in the literature, including the Matching Pursuit (MP) method [Bo 2013], the Orthogonal Matching Pursuit (OMP) method [Pati 1993] and the feature sign search method [Lee 2007]. The second issue consists in searching the appropriate dictionary that is an important question for the sparse representation approach. The choice of dictionary may be performed as follows:

- Either by constructing a predefined dictionary using mathematical functions such as Gabor, wavelets, curvelets and contourlets [Si 2010].
- Or by constructing a learned dictionary formed according to a set of training samples. This method does not employ generic mathematical functions and seeks to extract more precisely the complex structures from the data. In fact, learned dictionaries are suited to the class of the input signal to be processed and prove their efficiency in many applications.

5.2.2 Support Vector Machines (SVM)

Support Vector Machines (SVM) are proposed to solve problems of pattern recognition field [42]. In fact, this technique carries out pattern recognition in the case of two classes by making a decision area given using some points of the training data, named support vectors. Simultaneously, the decision area tends to indicate the largest margin, presented between two classes. Hence, the decision area was referred, in this case, to the optimal separating hyperplane and the nearest points to this separating hyperplane were represented as the support vectors as illustrated in figure 5.3. The optimal separating hyperplane is represented as the L line. As shown in figure 5.3, points placed on the lines L_1 and L_2 are support vectors.

The SVM is defined generally by the following equation:

$$f(x) = \text{sgn}\left(\sum_{i=1}^n \alpha_i c_i K(x, x_i) + s\right) \quad (5.6)$$

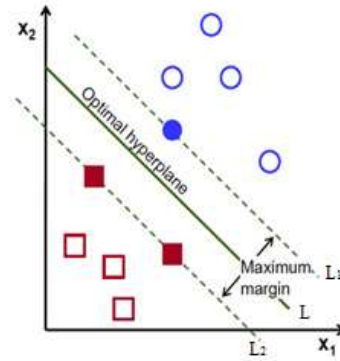


FIGURE 5.3: Separating hyperplane of the SVM.

where $c_i \in \{-1, 1\}$ is the class label of the trained x_i points in which class '1' means genuine distribution and class '-1' means impostor distribution, n is the total number of data points, coefficient α_i may be obtained by solving a quadratic problem, s is the bias and K represents the kernel function. In fact, basically four kernel functions are reported as follow:

- Linear function: $K(x, x_i) = x * x_i$,
- Polynomial function: $K(x, x_i) = [\gamma * (x * x_i) + c]^d$
- Gaussian function: $K(x, x_i) = exp(-\gamma ||x - x_i||^2)$
- Sigmoid function: $K(x, x_i) = tanh(ax * x_i + b)$

where γ and c are controlled coefficients and d is the polynomial degree.

5.3 Proposed identification approach based palmprint modality

5.3.1 Palmprint ROI extraction

In preprocessing step, it is important to localize the palmprint ROI containing principal lines and creases for palmprint feature extraction. In this work, palmprint ROI localization is performed according to the following steps:

1. Detect the centroid point of the hand followed by an orientation alignment according to the vertical axis passing through the centroid point.
2. Detect fingertips of the hand, as described in chapter 4, in order to make a rotation depending on the middle fingertip point.
3. Detect finger valleys using the new rotation of palmprint image and a reference line is formed using the two valleys points V_2 and V_3 placed around the middle finger intersecting the contour of the hand. The midpoint M_1 is then placed in the center between the point V_2 and the contour intersection point.
4. Repeat the third step for the second midpoint M_2 localization using V_3 and V_4 valleys (figure 5.4).
5. Link M_1 and M_2 midpoints and extract the square representing the palmprint ROI using M_1 and M_2 points.

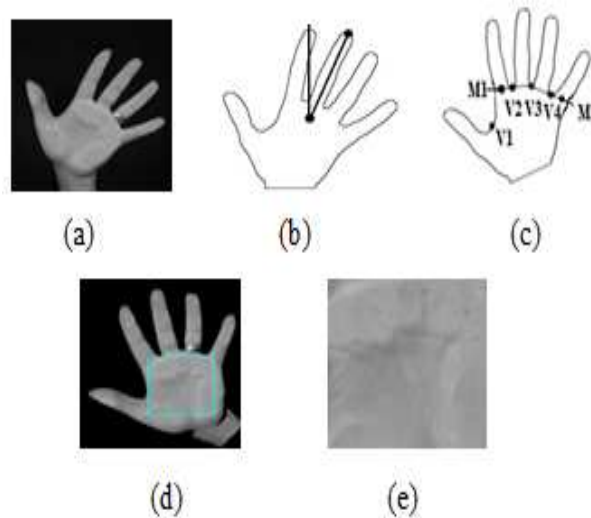


FIGURE 5.4: Palmprint segmentation:(a) Grayscale original image; (b) Orientation according to vertical axis; (c) Detection of midpoints M_1 and M_2 ; (d) Detection of palmprint ROI; (e) Palmprint image extraction.

5.3.2 Feature extraction

This section presents the description of palmprint ROI which characterizes better the palmprint. For this purpose, the texture information is taken into account to

propose a feature vector relative to each palmprint image. Several methods allow analyzing palmprint texture such as Wavelet transform, Fourier transform, Gabor filters, etc. In our palmprint identification method, SIFT descriptors are adopted due to their advantages of features invariance to geometrical transformations.

On the other hand, sparse representation (SR) is used to represent extracted SIFT descriptors. Indeed, recently, SR approach has proven its effectiveness in solving different tasks in computer vision field. In fact, SR is able to reveal semantic information of an image. The principal idea of SR consists of representing a signal $y \in \mathbb{R}^m$ as a linear combination of a small number of elements, named atoms, that are selected from a dictionary D , as follows:

$$y \approx D\alpha = \sum_{c=1}^P \alpha_c d_c \quad (5.7)$$

Where $D = [d_1, d_2, \dots, d_c]_{(c \in \{1, \dots, P\})} \in \mathbb{R}^{m \times P}$, $\alpha = [0, \dots, 0, \alpha_{j,1}, \alpha_{j,2}, \dots, \alpha_{j,s_c}] \in \mathbb{R}^P$ represents the coefficient vector in which non zero elements are affiliated only with the j -th class and P is the dimension of feature vectors which represent input images. If the number of classes is large, α in that case will be sparse.

Given a multimodal M -class classification problem in which Z biometric modalities are used. Consider each biometric modality is represented by s_i training images relative to each biometric modality $i = \{1, \dots, Z\}$ as $T^i = [t_1^i, t_2^i, \dots, t_M^i]$. The corresponding set of training with SIFT description $X^i = [x_1^i, x_2^i, \dots, x_M^i] = [x_{j,1}^i, x_{j,2}^i, \dots, x_{j,s_j}^i] \in \mathbb{R}^{s_j \times P}$ represents the training set of the i^{th} biometric trait, where $x_{j,s}$ represents the feature vector corresponding to the s -th sample image of the class j .

In multimodal biometrics problem, let a matrix of test samples Y of a biometric modality i . Each sample Y^i is represented by v_b observations $Y^i = [y_1^i, y_2^i, \dots, y_{v_b}^i] \in \mathbb{R}^{v_b \times P}$. The purpose is to determine to which class a test sample Y is belonging.

The learning of an overcomplete dictionary is performed from a number of SIFT descriptors randomly selected as training set. The Lagrange dual technique [Lee 2007] is employed to search the dictionary leading to the best possible representation of

each sample of training set with strict sparsity constraints. Firstly, a sign search algorithm is used in order to solve the problem of l_1 regularized least square while respecting the sparse vector α . Secondly, the Lagrange dual algorithm is employed in order to solve the problem of l_2 constrained least squares while respecting the dictionary D . Thus, a good dictionary may be found by solving the following optimization problem:

$$\begin{aligned} \min_{\alpha} \frac{1}{2} \|y - D\alpha\|_2^2 + \lambda \|\alpha\|_1 \\ \text{subject to } \|d_c\|_2 \leq 1, \forall c = \{1, 2, 3, \dots, P\} \end{aligned} \quad (5.8)$$

Where the dictionary D contains 1024 atoms with a dimension of 128 (same size of SIFT input) for each atom, so $D \in \mathbb{R}^{128 \times 1024}$, $\|\alpha\|_1$ represents the l_1 - norm of α and $\|d_c\|_2$ is the l_2 - norm constraint of d_c .

Hence, considering the SIFT description corresponding to an image $Y^i = [y_{(1)}^i, y_{(2)}^i, \dots, y_{(q)}^i]$, a sparse feature representation is formed via eq. 5.8 as $A^i = [\alpha_{(1)}^i, \alpha_{(2)}^i, \dots, \alpha_{(q)}^i] \in \mathbb{R}^{1024 \times q}$. The obtained sparse vectors are then quantized and a histogram representation is computed forming a SIFT sparse vector to each image.

5.3.3 Palmprint identification

SVM classification is extended to multi-class classification problems called multi-class linear SVM classifier [Yang 2009], in which we are interested since we deal with more than 100 classes. Considering a training data set $\{(u_p, v_p)\}_{p=1}^M$, $v_p \in V = \{1, \dots, M\}$, the aim of a linear SVM is to learn M linear functions $\{z_c^\top u | c \in V\}$, for example, given a test data u , its predicted class label is defined as:

$$v = \max_{c \in V} z_c^\top u \quad (5.9)$$

A one-versus-all method is taken to train M binary linear SVM allowing to solve the following unconstrained convex optimization problem

$$\min_{z_c} \{J(z_c) = \|z_c\|^2 + C \sum_{p=1}^n l(z_c; v_p^c, u_p)\} \quad (5.10)$$

where $v_p^c = 1$ if $v_p = c$, otherwise $v_p^c = -1$, and $l(z_c; v_p^c, u_p)$ represents a hinge loss function.

The differential quadratic hinge loss is taken as:

$$l(z_c; v_p^c, u_p) = [\max(0, z_c^\top u \cdot v_p^c - 1)]^2 \quad (5.11)$$

so that the training may be made readily using simple methods of gradient-based optimization.

5.4 Experimental evaluation

5.4.1 Proposed prototype

In our work, a new hand database has been built for experiment evaluation, in order to verify performances on Tunisian hands. Moreover, left and right hands have been acquired from the same person. In fact, the other hand databases present some weaknesses of having a different number of persons for both hands, preventing the matching between the left and right hands of the same person. In addition, others acquired only the left hand etc. So, REST (REgim Sfax Tunisia) hand database is proposed in order to solve these weaknesses. In fact, the acquisition is performed using a low cost digital Camera integrated in a Tablet (Samsung Tab 3) device. The captured left and right hand images are in RGB and have a size of 1536 * 1250 pixels, in low resolution of 72 dpi. The hands are placed in a comfortable way without any contact nor restriction of pegs or template, and the camera should be placed in front of the hand at approximately 50 cm in order to capture, simultaneously, hand and palmprint modalities. However, users are

asked to separate their fingers from each other and change angles between them, during acquisition. The lighting of hand images has been naturally diffused due to illumination variations inside the REGIM laboratory environment.

The images are collected from 150 subjects in the age group of 6-70 years, over a period of four months. In order to ensure the success of the image acquisition step, the subjects were just requested to place their hand entirely in front of a uniform dark background. Figure 5.5 presents examples of captured hand images of the proposed database.



FIGURE 5.5: Some examples REST hand database.

5.4.2 Experimental results

The proposed method is evaluated on three databases namely IITD hand database, CASIA palmprint database and the proposed REST hand database. Table 5.1 presents the influence of SIFT sparse representation method compared to other existing palmprint recognition methods in the literature, over the IITD hand database. In fact, Sun et al. [Sun 2005] extracted ordinal measures from palmprint images. The classification using hamming distance achieves CIR=85.58%. However, Jia et al. [Jia 2008] extracted robust line orientation code. The comparison between palmprint images using pixel-to-area comparison method obtains CIR=84.83%. On the other hand, Kumar and Shekhar's palmprint system [Kumar 2011b] is based on Gabor orientation features extracted from palmprint images. The classification at rank-level was performed using weighted Borda count method, achieving CIR=95%. Moreover, Luo et al. [Luo 2016] adopted local line directional patterns (LLDP descriptors) as features of palmprint images. The classification using Manhattan distance achieves CIR=92%. These studies are considered for comparison with the proposed SSRPI system because the same

database (IITD hand database) is employed for experiments evaluation. Consequently, the influence of the proposed SIFT sparse representation is remarkable from table 5.1 in terms of CIR by achieving better performances (CIR=96.73%) than other popular palmprint approaches.

TABLE 5.1: Comparison of the CIRs of the proposed approach and other popular approaches over IITD hand DB

Reference	Features	Classifier	CIR(%)
Sun et al., 2005 [Sun 2005]	Ordinal measures	Hamming distance	85.58
Jia et al., 2008 [Jia 2008]	Robust Line Orientation Code (RLOC)	Pixel-to-area comparison	84.83
Kumar and Shekhar, 2010 [Kumar 2011b]	Gabor orientation	Weighted Borda count	95.00
Luo et al., 2016 [Luo 2016]	Local Line Directional Patterns (LLDP descriptors)	Manhattan distance	92.00
Proposed SSRPI	SIFT sparse representation	SVM	96.73

In order to yet demonstrate the effect of the proposed SSRPI method, we have evaluated the proposed method using left and right palmprint of the proposed REST hand database, containing 1500 images. In fact, five images for left palmprint and five images for right palmprint are considered in our experiments. Table 5.2 reveals the CIR obtained over the proposed REST hand database for three and four training images. It can be seen that right palmprints offer better performances (CIR=93.33%) using 4 training images compared to left palmprints (CIR=88.33%).

TABLE 5.2: Correct identification rates over REST hand database

Instance	Train	Test	CIR (%)
Left palmprint	3	2	80.83
-	4	1	88.33
Right palmprint	3	2	90.13
-	4	1	93.33

To see the influence of left and right instances, the proposed SSRPI method is also assessed using the public CASIA palmprint database, containing 2400 palmprint

images. Experiments show better performances for left palmprints by achieving CIR=98.88% compared to right palmprints which obtain CIR=96.52%, using only two training images, as reported in table 5.3. Therefore, it is remarkable that left and right palmprints have different texture information since different identification rates are achieved. Moreover, the best reliability is not sufficiently observed between left and right palmprints, since it depends on the evaluated database (in the case of REST database, right palmprints achieve better performances, whereas, in the case of CASIA database, left palmprints obtain better performances). This will encourage us to fuse these two instances in order to increase the accuracy and reliability of the proposed method, as will be described in the next chapter.

TABLE 5.3: Correct identification rates over CASIA palmprint database

Instance	Train	Test	CIR (%)
Left palmprint	3	2	99.17
-	2	3	98.88
Right palmprint	3	2	97.70
-	2	3	96.52

It is necessary to compare the SSRPI method with popular palmprint methods existing in the literature. Table 5.4 displays a comparison in terms of CIR over the public CASIA palmprint database. In fact, Jia et al. [Jia 2008] have achieved CIR=97.60% using RLOC features extracted from palmprint images. On the other hand, Zuo et al. [Zuo 2010] extracted sparse multiscale competitive code (SMCC) from palmprint images. This method employed, firstly, the sparse representation in order to achieve the robust estimation of the local orientation of palm lines. Secondly, it extends the competitive rule and encodes the calculated sparse codes, which generates a compact representation of multiscale features. The SMCC method achieved CIR=98.74% using 600 palms of left and right hands.

Recently, Yue et al. [Yue 2014] have presented an accurate and fast palmprint identification system based on a consistent orientation pattern (COP) hashing method. In fact, principal lines are represented as stable features in palmprint images, so the orientation features should be more consistent compared to others. Moreover, since principal lines are dark and thick, they may be represented by

the orientation features with low filter responses. Indeed, the consistency analysis is based on the selection of the more consistent orientation features, allowing a fast identification process. Experiments achieved CIR=96.40% using the public CASIA palmprint database.

On the other hand, Hammami et al. [Hammami 2014] proposed a persons identification approach using palmprint biometric modality. This approach was based on the partition of the entire palmprint image into sub-regions. Then, the LBP (Local Binary Pattern) operator has been employed in order to describe the texture information of each sub-region. Finally, a set of sub-regions has been selected to consider only the most discriminating regions for identification. Experiments of this approach obtained CIR=97.53% by extracting LBP features and CIR=96.33% by extracting SIFT features, from the selected palmprint sub-regions, over CASIA palmprint database.

Thus, it can be observed from table 5.4 the efficiency of the proposed SSRPI method by achieving better identification rate (CIR=99.17%) than the other palmprint approaches.

TABLE 5.4: Comparison of the CIRs between the proposed approach and other popular palmprint approaches over CASIA palmprint DB

Reference	Method	CIR (%)
Jia et al., 2008 [Jia 2008]	Robust line competitive code (RLOC)	97.60
Zuo et al., 2010 [Zuo 2010]	Sparse multi-scale competitive code (SMCC)	98.74
Yue et al., 2013 [Yue 2014]	Consistent orientation pattern (COP) hashing	96.40
Hammami et al., 2014 [Hammami 2014]	-LBP features -SIFT features	97.53 96.33
Proposed SSRPI	SIFT Sparse representation	99.17

TABLE 5.5: Execution time

Steps	Execution time (ms)
Preprocessing	768
SIFT Feature extraction	534
Sparse representation	565
Identification	29
Total	1896

5.4.3 Execution time performance

The proposed method is implemented using Matlab 2014a on a computer with 2.5 GHz, Intel core i3 CPU and 4GB RAM. Table 5.5 listed the execution time relative to each step. Hence, the proposed palmprint identification method requires 1.9s of total execution time.

5.5 Conclusion

The proposed palmprint identification method is described. In this method, the palmprint biometric trait is represented using SIFT sparse representation method. This descriptor has proven its efficiency by achieving promising performances which are competitor to existing palmprint recognition approaches.

The next chapter will display the different proposed hand multi-types fusion of hand shape and palmprint biometric modalities.

Chapter 6

Proposed hand multi-types fusion for multimodality

Contents

6.1	Introduction	108
6.2	Multi-representation hand shape verification method	109
6.2.1	Feature extraction module	110
6.2.2	Matching score	110
6.2.3	Information fusion method	111
6.2.4	Experiments and results	111
6.3	Multi-biometric hand recognition method	115
6.3.1	Hand shape and palmprint fusion for persons verification	115
6.3.1.1	The proposed Sift Matching Refinement based PalmPrint Verification (SMRPPV)	115
6.3.1.2	Information fusion and decision	117
6.3.1.3	Experiments and verification results	118
6.3.2	Hand shape and palmprint fusion for persons identification	121
6.3.2.1	Information fusion	121
6.3.2.2	Experiments and results	124
6.4	Multi-instance palmprint identification method	131
6.4.1	Fusion at rank level using probability distribution	131
6.4.1.1	Probability knowledge basis	132
6.4.1.2	Probability distributions of the scores	133
6.4.2	Experimental evaluation	135

6.5	Summary and conclusion	137
------------	---	------------

6.1 Introduction

This chapter presents the proposed multi-types hand fusion for multimodality including multi-representation, multi-biometric and multi-instance fusion, as shown in figure 6.1. Moreover, the different fusion schemes treated in our work are presented and discussed. Figure 6.2 presents the fusion schemes treated in this work represented by ✓ vs. existing fusion schemes. Finally, experiments and results of each fusion type are demonstrated in section 6.4.2.

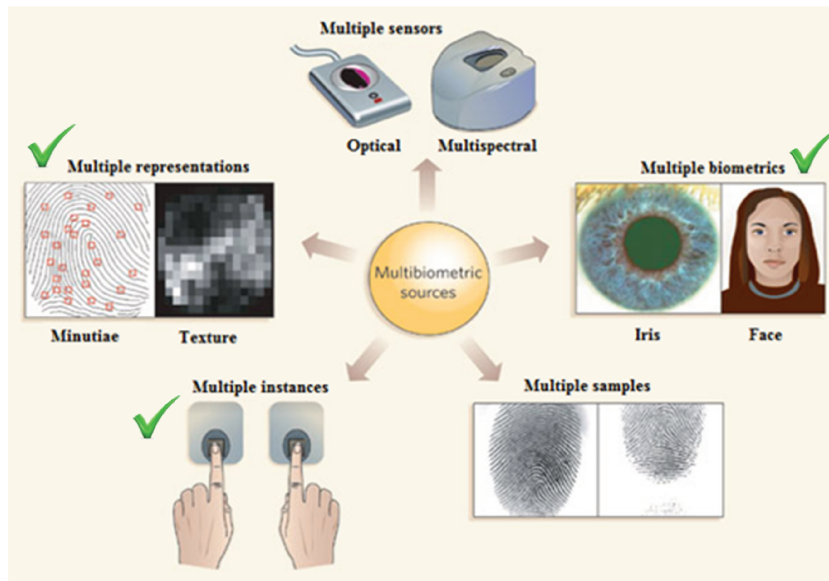


FIGURE 6.1: Overview of the different multi-types treated in our work.

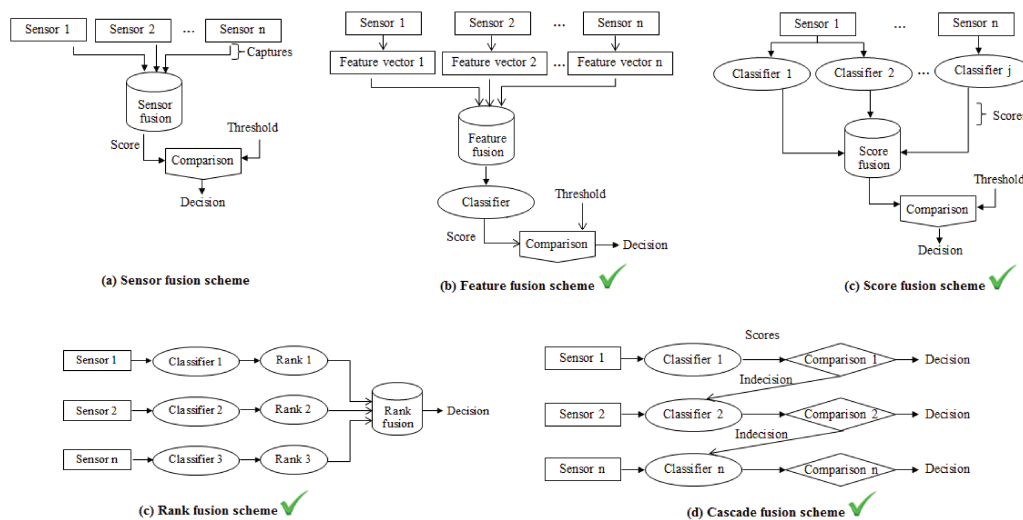


FIGURE 6.2: Overview of the different fusion schemes treated in our work.

6.2 Multi-representation hand shape verification method

In this section, we describe the proposed multi-representation hand shape verification method combining shape and geometry descriptors extracted from hand modality, namely, SIFT descriptors and geometrical features (figure 6.3).

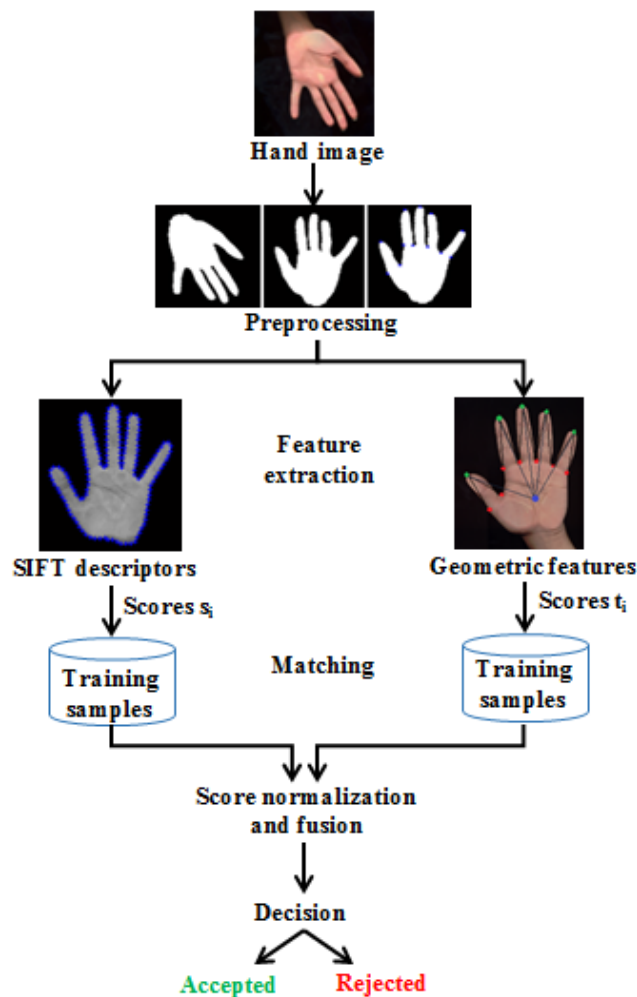


FIGURE 6.3: Flowchart of the proposed multi-representation method.

The preprocessing module is based on the segmentation of the hand and the detection of finger tips and valleys as described in chapter 4.

6.2.1 Feature extraction module

SIFT descriptors are extracted from hand shape modality, as described in chapter 4. It consists of detecting keypoints localized on the contour of the hand for further SIFT description. The second type of features incorporates the geometrical measurements of the hand including size of the palm, length and width of fingers, etc. In fact, we investigate 15 geometrical distances of the hand, computed using Euclidean distance according to the localized landmark points. These features represent:

- 10 fingers deviations (2 deviations for each finger) which present the distance between fingertip and two finger valleys.
- 5 distances computed from the center point of the hand to the five fingertips.

6.2.2 Matching score

An input image is represented as a set of features (a feature vector) and is then compared with the claimant's hand image stored in database for identity verification. Therefore, a distance metric should be applied to compute the similarity measure between the two feature vectors.

In our hand biometric system, two different descriptors are extracted from hand images. Concerning geometrical features, the Euclidean distance is used to compute the similarity measure between feature vectors. If the distance is higher than a certain threshold value t , then these two vectors belong to different individuals; otherwise, they are from the same individual.

On the other hand, with regards to SIFT features extracted from hand shape, the cosine similarity measure between the input and the enrolled image [Lowe 2004] is calculated. The number of matched points between images is considered as the matching score. If the score is lower than a certain threshold value t_1 , these two images are from different persons; otherwise, they are from the same person.

In order to provide a unique matching score, scores obtained from hand geometry and hand shape matching modules have to be normalized before combination to

make them in the same range of values. The normalization of scores is performed using the min-max normalization method, expressed as follows:

$$s_{in} = \frac{s_{in} - \min(s_i)}{\max(s_i) - \min(s_i)} \quad (6.1)$$

Where max and min represent functions generating, respectively, the maximum and the minimum value of the score s_i of the training set.

6.2.3 Information fusion method

Information fusion is presented as a promising strategy to improve the accuracy of a biometric system. It may be applied at different levels including sensor, feature, score and decision.

In this work, we propose to implement score level fusion based on weighted sum rule method. In fact, the weighted sum rule method has been well studied by researchers in the literature [Kang 2014] since it is the most straightforward fusion method at matching score level. It is based on the computation of the similarity measure between two hand images by fusing scores obtained from different processes using different weights. So, the final score is computed as follows:

$$S_{fusion} = w_a \times S_{HG} + w_b \times S_{HS} \quad (6.2)$$

Where w_a and w_b are the weights affected to hand geometry score and hand shape score, respectively. The unit-sum constraint is satisfied, as $w_a + w_b=1$.

6.2.4 Experiments and results

The evaluation of the multi-representation method is performed using the Bogazici University hand database [Yoruk 2006a]. Hand images are acquired using a commercial scanner from 642 individuals with hands placed flat on the glass platen. Three samples are captured from each hand at different times. The first two images for each subject were used for training and the rest were used for testing.

Thus, a total of 1284 (642×2) genuine and 823044 ($642 \times 641 \times 2$) imposter matching scores were provided using the test data.

To assess the performance of the proposed system, false acceptance rate (FAR) and false rejection rate (FRR) are adopted based on scores obtained in matching score module to generate the final decision of all the samples. Several sets of FRR and FAR are achieved using different threshold values in order to plot the Receiver Operating Characteristic (ROC) curve as illustrated in figure 6.4. The trade-off between FAR and FRR represents the equal error rate (EER).

In our experiments, the fusion of hand shape and hand geometry is carried out.

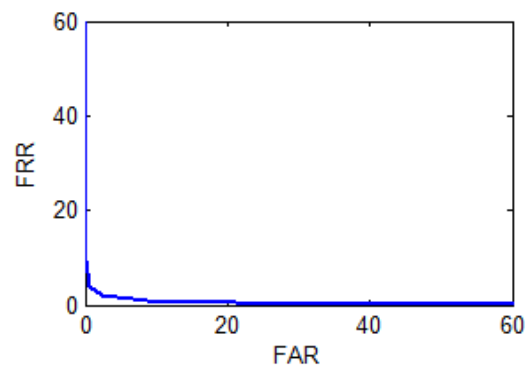


FIGURE 6.4: ROC curve of FAR and FRR relative to matching score fusion results.

The ROC curve for three different cases including hand shape alone, hand geometry alone and fusion of hand shape and hand geometry using weighted sum rule method at matching score level, are shown in Figure 6.5.

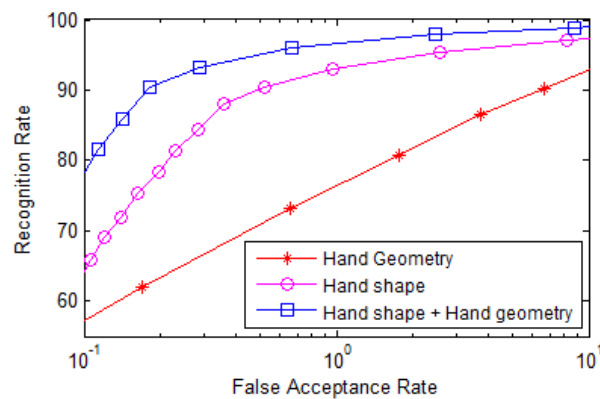


FIGURE 6.5: Comparative performance of hand geometry and hand shape features using score level fusion.

TABLE 6.1: Performance verification rates (%).

	FAR	FRR	RR	EER
Hand shape	2.56	4.67	95.25	4.05
Hand geometry	8.39	7.86	92.06	8.09
Hand shape + Hand geometry (simple sum rule)	3.97	2.1	97.64	3.01
Hand shape + Hand geometry (Weighted sum rule)	2.46	2.1	97.82	2.25

In this system, we adopted two fusion methods to compare verification results namely simple sum rule and weighted sum rule methods. This comparison is given in table 6.1. Regarding weighted sum rule method, the final score is obtained using different weight sets. Experimentally, the optimal weights are achieved when $EER=2.25\%$ ($w_a=0.32$ and $w_b=0.68$).

Table 6.2 shows a comparison of our system with other existent approaches in term of EER. Indeed, Kang and Wu [Kang 2014] have achieved 3.69% of EER by fusing Fourier descriptors and finger area functions extracted from fingers geometry that are acquired from 638 subjects. However, Sharma et al. [Sharma 2015] have obtained 0.52% of EER by combining hand shape (wavelet decomposition) and hand geometry (7 geometric distances) using 240 subjects. Since our results are achieved using a larger database containing 642 subjects, the performance obtained from the proposed system ($EER=2.25\%$) is competitive and encouraging results are provided.

TABLE 6.2: Performance comparison with different approaches in term of equal error rate (EER).

Reference	Features	Algorithms	Population size	EER (%)
Yoruk et al. [Yoruk 2006a]	Hand contours (Bogazici db)	Modify Hausdorff Distance and ICA	458	≈ 2
Luque-Baena et al. [Luque-Baena 2013]	Hand geometry (IITD db)	GA-LDA	100	4.51
Sharma et al. [Sharma 2015]	Hand shape + geometry (IITD db)	7 geometric distances and wavelet decomposition	240	0.52
Kang and Wu [Kang 2014]	Four fingers geometry features (Bogazici db)	Fourier descriptors and finger area functions	638	3.69
Proposed	Hand shape + geometry (Bogazici db)	SIFT descriptors and 15 geometrical features	642	2.25

6.3 Multi-biometric hand recognition method

6.3.1 Hand shape and palmprint fusion for persons verification

A fusion of hand shape and palmprint biometric system for persons verification is proposed. The hand shape verification method described in chapter 4 is considered. While palmprint verification method is detailed in this section as well as the proposed fusion process.

6.3.1.1 The proposed Sift Matching Refinement based PalmPrint Verification (SMRPPV)

The unimodal Palmprint verification system contains four principal stages namely the preprocessing, the feature extraction and matching, the SIFT matched keypoints refinement and the decision stage. The proposed SMRPPV is illustrated in figure 6.6.

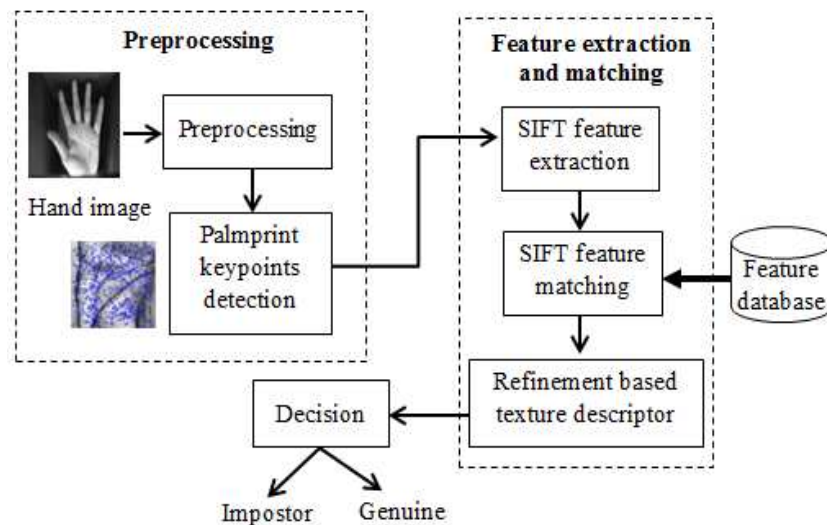


FIGURE 6.6: The proposed SMRPPV system

After preprocessing step and palmprint ROI extraction, the standard SIFT method, detailed in section 4.2.1, is employed for keypoints detection and description in order to depict the local texture of palmprint biometric trait. Nevertheless, the

matching of keypoints between two palmprint images and the decision of persons verification according to the number of matched keypoints is not a good way to discriminate a person from another. Consequently, as for hand shape verification method, we adopt a SIFT matching refinement process in order to describe distinguishable palmprint features based on texture features. In fact, these features are extracted from matched points using a patch image forming the Gabor Palmprint Feature (GPF). The GPF of a keypoint $k(x, y)$ at (x, y) is presented as the feature vector of the square patch image centered at (x, y) , based on Gabor filters described in section 4.2.2. The matching between two square patch images p_1 and p_2 of two matched keypoints is performed using Euclidean distance method. This distance is represented as d . If d is less than a certain threshold δ_1 , these keypoints are truly matched. Otherwise, they are falsely matched and should be removed. The distance formula is as follows:

$$d = \sqrt{(p_1 - p_2)^2} \quad (6.3)$$

The total number of SIFT keypoints properly matched is considered as the final score in order to make final decision of our SMRPPV system.

Algorithm 2: Keypoint matching refinement process for palmprint recognition

Input:

1. Two matched palmprint images $P_1(x_1, y_1), P_2(x_2, y_2)$
2. Matched keypoints set: $M = \{(i, q)^l | l = \{1, 2, \dots, nb\}\}$ where $(i, q)^l$ represents the l^{th} pair of matched keypoints and nb is the pairs number of matched keypoints

Output:

K_2 : New set of matched keypoints after refinement

N_2 : Number of refined matched keypoints

1. Initialization: $B_{fm} = \emptyset$ (fm: false matched points)
 2. **for** $s = 1$ **to** nb **do**
 - (1) Compute GPF_i, GPF_q for keypoints i, q with $(i, q)^t \in B_{fm}$ using eq.4.6
 - (2) Match GPF_i, GPF_q and compute the distance d_1
 - (3) **if** $d_1 > \delta_1$ **then**
 - (a) Remove $(i, q)^t$
 - (b) $B_{fm} = B_{fm} + (i, q)^t$
 - (c) $nb = nb - 1$
 3. $K_2 = M - B_{fm}$
 4. $N_2 = nb$
-

6.3.1.2 Information fusion and decision

In this section, the fusion process of hand shape and palmprint biometric traits at matching score level for person's identity verification is presented. In fact, matching scores are obtained from the different modalities. Regarding SIFT features extracted from hand images, they are matched with the enrolled template based on Euclidean distance and even the case of palmprint SIFT features. Thus, after matching refinement steps adopted for hand shape and palmprint biometric systems, the two scores obtained from these two systems are inputted to the training phase of the binary SVM classifier, described in section 5.2.2, in order to generate the final decision about the identity of the person. Indeed, the research of palmprints and hand shapes verification operates concretely with small samples. For this reason, we employ Support Vector Machines (SVM) for identity verification due to its great performances in various learning problems. If classes provided from the hand shape verification method (SMRHSV) and the palmprint verification (SMRPPV) method are different, fingers texture are thus extracted from the hand image in order to generate the final decision. The general fusion process is shown in figure 6.7.

A. Fingers segmentation The segmentation of fingers Regions of Interest (ROI) requires the decomposition of each finger apart. In fact, finger tips and valleys have to be located to extract the finger from the hand. Hence, the method described in [Yoruk 2006b] is used in order to seek minima and maxima of contour to find extremities of the hand silhouette. Thus, five maxima (fingertips) and four minima (finger valleys) are detected. Moreover, three additional points are located in thumb, index and little extremities (symetric points of thumb, index and little finger valley points) which intersect contour to draw the reference line of each finger as demonstrated in figure 6.8.

B. Feature extraction and fusion process Gabor filters are extracted from each finger surface. A matching process between test images and enrolled images (of persons generated from hand shape and palmprint systems) is carried out and five scores are produced using Euclidean distance. Furthermore, the five scores

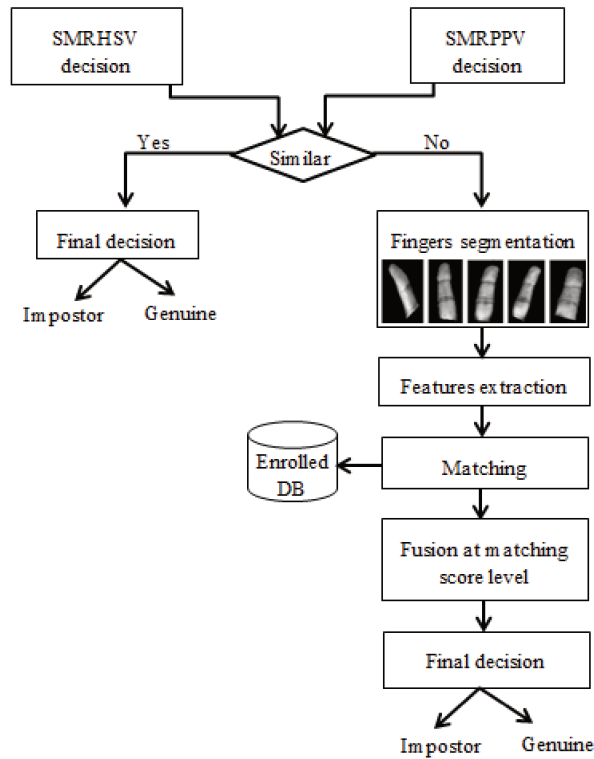


FIGURE 6.7: Fusion scheme.

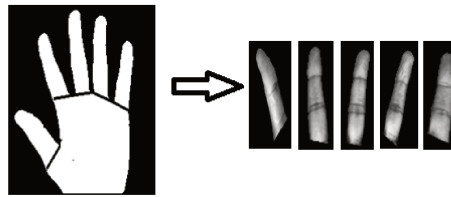


FIGURE 6.8: Fingers segmentation.

are fused using simple sum rule in order to produce a single score for each hand sample. The final decision is made only if hand shape and palmprint systems generate different decisions (figure 6.7).

6.3.1.3 Experiments and verification results

In our experiments, the IITD Touchless hand database (described in section 3.2.1) is employed, containing 1150 hand images captured from 230 subjects. Each person is represented by 5 images which are divided into three images used for training phase and two images used for testing phase.

In this work, hand shape, palmprint and fingers modalities are adopted in order to verify the identity of the person.

Concerning palmprint biometric modality, original SIFT method is used to extract SIFT descriptors. A refinement process is also adopted after the matching step in order to refine as much as possible false matched keypoints between two palmprints. This refinement process is carried out according to texture features around matched keypoints. The proposed SMRPPV system presents an EER = 4.31% which is promising compared to results of SIFT algorithm without refinement (EER = 5.43%) and the system of Kumar and Shekhar which achieved an EER = 5.02% as shown in table 6.3.

TABLE 6.3: Comparison of verification results of palmprint systems.

Methods	EER (%)
SIFT algorithm without refinement	5.43
Gabor orientation features [Kumar 2011a]	5.02
Proposed SMRPPV system	4.31

The proposed multimodal system works essentially by fusing hand shape and palmprint modalities. The fingers surfaces are embedded only if decisions produced from hand shape and palmprint are different. Therefore, two scores are obtained and fused using different fusion methods including max rule, product rule, sum rule and SVM classifier in order to make the final decision. Two-thirds the IITD hand DB is used for training and one-third is used for testing. Experiment results demonstrated that the highest recognition rate is obtained using SVM classifier, as shown in table 6.4.

Table 6.5 reports performance verification rates relative to unimodal systems, bimodal system and multimodal system. In fact, the proposed bimodal system fusing hand shape and palmprint modalities present an EER=1.31% and a RR=98.63%. On the other hand, the proposed multimodal system fusing hand shape, palmprint and fingers modalities present an EER=0.19% and an RR=99.82%.

TABLE 6.4: Performance verification rates with different fusion methods of hand shape and palmprint modalities.

Method of fusion	FAR (%)	FRR (%)	RR (%)	EER (%)
Max rule (without refinement)	2.01	2.82	97.17	2.87
Max rule (after refinement)	1.63	2.60	97.39	2.23
Product rule (without refinement)	3.19	3.26	96.73	3.22
Product rule (after refinement)	2.92	2.82	97.17	2.87
Sum rule (without refinement)	3.65	2.16	97.24	2.90
Sum rule (after refinement)	2.76	1.73	98.26	2.24
SVM classifier (without refinement)	1.83	1.47	98.38	1.65
SVM classifier (after refinement)	1.34	1.28	98.63	1.31

TABLE 6.5: Performance verification rates.

	FAR (%)	FRR (%)	RR (%)	EER (%)
Hand shape	4.42	3.44	96.15	3.93
Palmprint	4.36	4.56	95.26	4.31
Hand shape + Palmprint	1.34	1.28	98.63	1.31
Hand shape + Fingers + Palmprint	0.16	0.02	99.82	0.19

A comparison of our system with other existing approaches as well as our previous approaches, in terms of EER, is outlined in table 6.6. All the methods cited in this table used the IITD hand DB as in the proposed approach. Indeed, Kong and Zhang [Kong 2004] have achieved 3.41% of EER using compcode features of palmprint traits. However, Charfi et al [Charfi 2014] have obtained 1.80% of EER by combining hand shape and palmprint features. On the other hand, our previous work [Charfi 2015a] combines hand shape, palmprint and fingers, at the same time, and an EER=1.95% is achieved. Thus, the proposed system presents the merit of reducing the complexity of the algorithm by inputting fingers only if the bimodal system generate an uncertain decision.

TABLE 6.6: Performance comparison with different approaches in term of equal error rate (EER) using IITD hand database.

Features	Algorithms	EER (%)
Hand shape + Palmprint + Fingers features	SIFT features and Gabor features	1.95
Hand shape + Palmprint features	SIFT features	1.80
Matching refinement of Hand shape + Palmprint + Fingers fusion	Matching refined SIFT descriptors and Gabor features	0.19

6.3.2 Hand shape and palmprint fusion for persons identification

6.3.2.1 Information fusion

The proposed fusion scheme is presented in this section. Several kinds of multi-modal biometric systems are developed in literature [Kumar 2006a, Prasad 2009, Ferrer 2011] which are based on a combination of hand geometry and palmprint images, at feature, score or decision level, for person recognition. Unlike other works that adopt either a single fusion level or various fusion levels independently, our fusion scheme is grounded on a cascade architecture with hybrid fusion. In fact, the feature level fusion and decision level fusion are employed to combine hand shape and palmprint modalities. Each unimodal system generates one decision about the identity of the corresponding person, after classification task. Hence, the hand shape unimodal system provides a feature vector V_{HS} and a decision D_{HS} and the palmprint unimodal system provides a feature vector V_{PP} and a decision D_{PP} . If D_{HS} and D_{PP} are similar, then the final decision (identity) is generated. Otherwise, the feature level fusion is performed by the concatenation of the feature vectors V_{HS} and V_{PP} to form the feature vector V_{FF} for the fused

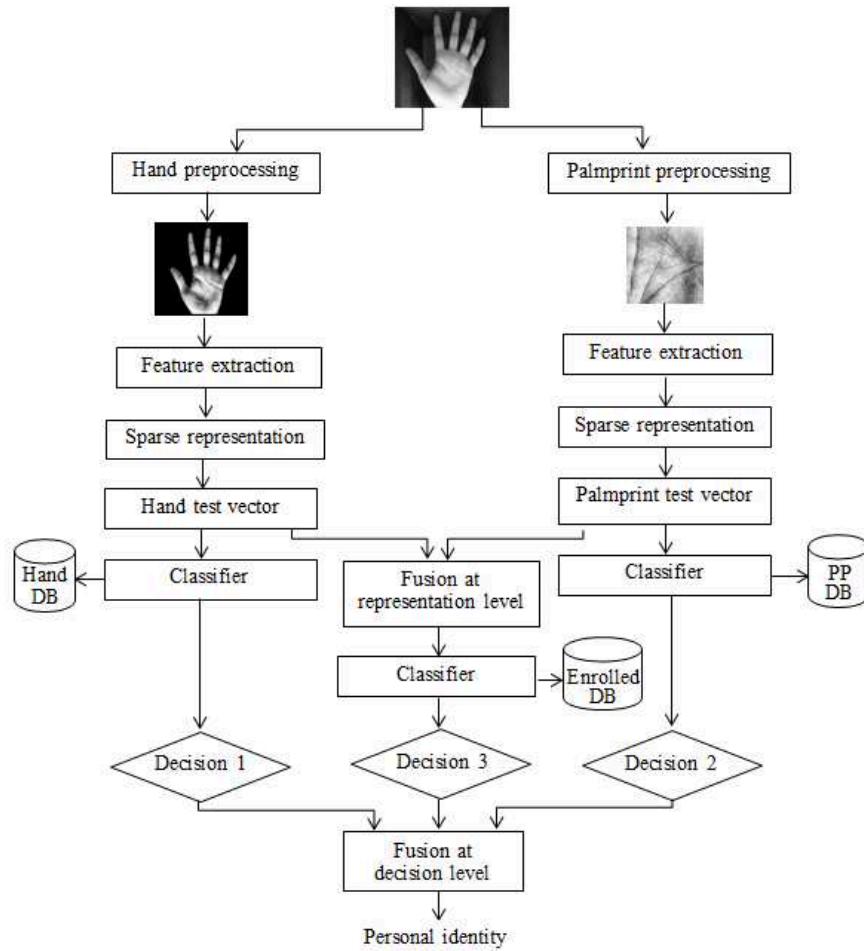


FIGURE 6.9: Block diagram of the proposed identification system.

hand representation as follows:

$$V_{FF} = [V_{HS} \quad V_{PP}] \quad (6.4)$$

It is noted that the normalization step is not needed since V_{HS} and V_{PP} present the same type of features.

The combined feature vector V_{FF} is classified and compared to fuse feature vectors of training images, using SVM classifier. This classification generated a decision D_{FF} about the identity of the person, as shown in figure 6.10. The obtained decisions D_{HS} , D_{PP} and D_{FF} are then fused using majority voting in order to generate the final decision. If D_{HS} , D_{PP} and D_{FF} are different, the k-Nearest Neighbor (k-NN) classifier is employed to classify the feature fusion vector V_{FF} compared to training images corresponding to the three decisions D_{HS} , D_{PP} and

D_{FF} . In fact, k-NN classifier consists in finding the k closest examples to the new example, according to a similarity measure. In our work, the 1-NN classifier is adopted in order to generate a single class concerning the identity of the person. On the other hand, the similarity measure is computed using the Euclidean distance expressed as follows:

$$dist_t = \sqrt{(V_{FF} - V_{TRt})^2} \quad (6.5)$$

where V_{TR} represents the combined training feature vectors of decisions D_{HS} , D_{PP} and D_{FF} , and $t=\{1, \dots, T\}$ is the number of training feature vectors.

The proposed fusion process is detailed in algorithm 3. The credit of the proposed fusion process is the gain of execution time, since it is not necessary to go through all steps if the two biometric modalities provide the same person's identity from the beginning.

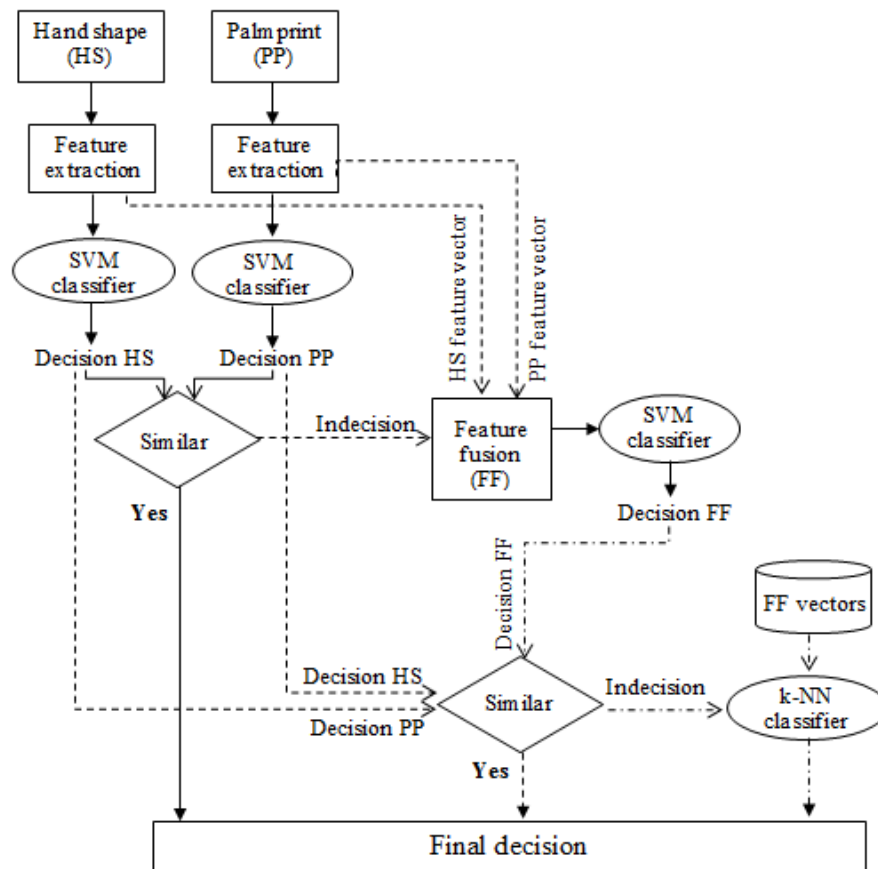


FIGURE 6.10: Architecture of the proposed fusion scheme.

Algorithm 3: *The proposed fusion process*

Input:

1. Feature vector V_{HS} relative to hand shape modality
2. Feature vector V_{PP} relative to palmprint modality
3. Training feature vectors of hand shape and palmprint modalities V_{FFi}

Output:

C : Class (person's identity) corresponding to the test hand image

1. $C = \emptyset$
 2. D_{HS} = Classify V_{HS} by SVM classifier
 3. D_{PP} = Classify V_{PP} by SVM classifier
 4. **if** $D_{HS} = D_{PP}$ **then**
 - $C = D_{HS}$
 - else**
 - D_{FF} = classify V_{FF} by SVM classifier
 - if** $(D_{HS} = D_{FF})$ **OR** $(D_{PP} = D_{FF})$ **then**
 - $C = D_{FF}$
 - else**
 - for** $t = 1 : T$ **do**
 - Matching between test feature vector V_{FF} and V_{TRt} using the
 - Euclidean distance measure ($dist_t$)
 - $C =$ 1-Nearest Neighbor ($dist_t$)
 5. Return class C
-

6.3.2.2 Experiments and results

The evaluation of this system is performed using the Bogazici University hand database [Yoruk 2006a], containing 1845 images, and the IITD Touchless hand database [Kumar 2008], [Kumar 2011a], containing 1150 images.

The hand identification experiments, based on hand and palmprint images, were carried out on two different population sizes selected from each database, consisting of 100 and 230 subjects for IITD hand database and 200 and 615 subjects for Bosphorus hand database. This choice is justified by the fact that these population sizes were among the most employed in the literature. Moreover, various population sizes help us to observe the identification performance with the increasing number of subjects. In addition, different number of training images help us to see the effect of persuasiveness of the proposed system with small number of training images. Therefore, we evaluated the proposed system using 3 and 4

training images for IITD hand database and 2 training images for Bosphorus hand database.

Our first experiment concerns the number of detected keypoints for hand shape modality, selected with higher rate of identification. This identification rate is measured as the rate of testing samples successfully classified. It represents the number of correct identified samples divided by the global number of samples, which consists of results after identification phase. These results are represented by the Correct Identification Rate (CIR) used as evaluation criterion. Thus, the proposed unimodal SIFT-based Sparse Representation for hand shape Identification (SSRHSI) system is based chiefly on trying different number of keypoints including 150, 200 and 300 keypoints localized on the contour of the hand. The rationale of the choice of these numbers of keypoints is that redundant points in the contour are removed, so we aim to reduce as much as possible the number of keypoints to decrease the computational complexity of the feature extraction step. On the other hand, the choice of a small number of keypoints like 50 or 100 may reduce information concerning the shape of the hand, which yields lower accuracies. Table 6.7 exhibits results of varying the number of keypoints compared to standard SIFT keypoints, over IITD hand database. This table reveals that 300 keypoints offer higher identification rates for different population sizes (100 and 180 subjects) and different number of training images (3 and 4 images) than 150, 200 and standard SIFT keypoints, which justify our selection of 300 keypoints. This number was also considered for hand images of Bosphorus hand database, and better results are obtained compared to standard SIFT keypoint detection especially for 615 subjects using 2 training images, as shown in table 6.8.

In our SSRHSI system, SIFT descriptors are extracted from the selected 300 keypoints and sparse representation is employed in order to combine linearly SIFT descriptors to form one feature vector for each hand image. In our experiments, each hand image is resized to a 256×256 image. For each image, SIFT descriptors are extracted for each 16×16 patches which were sampled on a grid with 8 pixels of step size. Therefore, each patch is centered by the considered keypoint. The dictionary is learned from random SIFT patches and its size is defined to be 1024.

TABLE 6.7: Correct identification rates, CIR (%) of the different keypoints detection for various population size of IITD hand database

Method	Number of keypoints	Train (%)	Test (%)	CIR (%)	
				100	230
Proposed system using standard SIFT keypoints detector	-	60	40	73.16	79.20
		80	20	80.33	85.21
Proposed system using proposed keypoints detector	150	60	40	89.66	91.85
		80	20	94.33	94.71
	200	60	40	93.33	96.33
		80	20	96.33	96.52
300	60	40	95.16	96.15	
	80	20	97.33	97.82	

TABLE 6.8: Comparison of hand shape CIR (%) between different detected keypoints using Bosphorus hand DB

Method	Population size	
	200	615
Proposed system using standard SIFT keypoints detector	81	76.15
Proposed system using proposed keypoints detector	80.66	83.17

In fact, experimentally, we tried two sizes: 512 and 1024. The performance of size 1024 increases compared to 512 by obtaining 96.15% for 1024 size and 95.24% for 512 size. Higher size of dictionary (for example 2048) will increase the dimension of feature vector especially after feature fusion of hand shape and palmprint modalities. For this reason, the dictionary is fixed to 1024. Once the dictionary is learned, the sparse representation feature is efficiently formed for each image. The identification phase is performed using Linear SVM classifier. Table 6.9 reports the influence of SIFT sparse representation method compared to other existing hand shape recognition methods in literature, over the IITD hand database. In this respect, Ferrer et al. [Ferrer 2011] extracted 400 finger widths. The classification using Least SVM achieves a CIR=94.72%. On the other hand, Luque-Baena et al. [Luque-Baena 2013] extracted 403 geometrical features from the whole hand. These features were then selected using Genetic algorithms method. The classification using SVM classifier achieves a CIR=86.60% evaluated on 230 subjects of IITD hand database. The proposed SSRHI system is also compared to our previous system, in which SIFT descriptors were extracted from hand images and the

cosine similarity method was adopted for the matching step. The CIR=94.14% is obtained using our previous system. These works are considered for comparison because their experiments were evaluated using the same database adopted in the proposed work. Thus, it can be seen from table 6.9 that the proposed SIFT sparse representation proves its efficiency since it offers better performances (CIR=96.16%) than other descriptors.

TABLE 6.9: Comparison of hand shape biometric system performance vs. an existing system in the literature using IITD hand DB

Reference	Features	Classifier	CIR(%)
Ferrer et al., 2013 [Ferrer 2011]	400 finger widths	Least Square SVM	94.72
Luque-Baena et al., 2013 [Luque-Baena 2013]	Geometrical features	SVM	86.60
Charfi et al. [Charfi 2014]	SIFT descriptors	Cosine similarity	94.14
Proposed SSRHI	SIFT + sparse representation	SVM	96.15

Our second experiment concerns the proposed fusion scheme of our SIFT Sparse Representation for Hand Shape and Palmprint identification (SSRHSPi) system. Table 6.10 reveals performance results of the fusion at representation level as well as the cascade fusion at feature and decision levels, over IITD hand database. The fusion at representation level achieves a CIR=98.33% for 100 subjects and 99.27% for 230 subjects, using 3 training images. However, the cascade fusion achieves a CIR=99.5% for 100 subjects and CIR=99.57% for 230 subjects. Thus, it can be seen from table 6.10 that the performance of the proposed system is increased or maintained with increasing the number of subjects, which proves the robustness of the proposed identification system.

On the other hand, table 6.11 reports results obtained by the fusion at representation level and the cascade fusion at feature and decision levels, over Bosphorus hand database. In fact, the CIR is slightly reduced with increasing the number of subjects by obtaining CIR of 98.16% for 200 subjects and 96.04% for 615 subjects, for fusion at representation level. Regarding the cascade fusion, CIR is also slightly decreased by achieving 98.5% for 200 subjects and 97.61% for 615 subjects.

TABLE 6.10: CIR (%) of the proposed system using IITD hand DB

Modality	Population size	
	100	230
Hand shape	95.16	96.15
Palmprint	96.66	96.73
Hand shape + Palmprint based on fusion at feature level	98.33	99.27
Hand shape + Palmprint based on cascade fusion at feature level and decision level	99.50	99.57

This reduction is intuitively explained by the effect that the difference between population sizes is large (415 subjects) and the number of training images is small (2 training images).

TABLE 6.11: CIR (%) of the proposed system using Bosphorus hand DB

Modality	Population size	
	200	615
Hand shape	82.44	80.12
Palmprint	97.5	94.95
Hand shape + Palmprint based on fusion at feature level	98.16	96.04
Hand shape + Palmprint based on cascade fusion at feature and decision levels	98.50	97.61

Figure 6.11 shows the evolution of CIR with increasing subject numbers of the IITD hand DB using the proposed SSRHPI system.

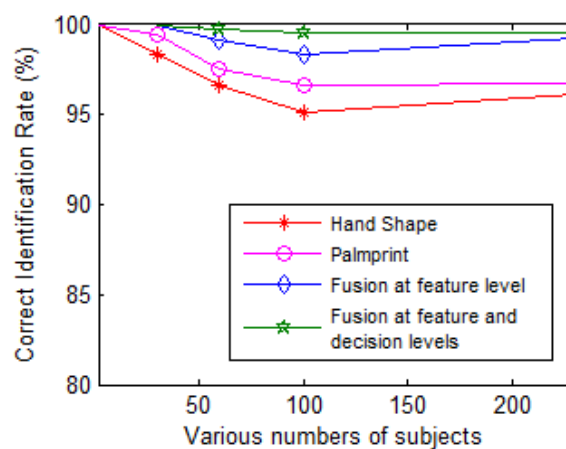


FIGURE 6.11: Correct Identification Rate (CIR) in terms of different numbers of subjects of IITD hand database.

The proposed system is compared to other existing multimodal hand biometrics fusing hand shape/geometry and palmprint modalities. Yoruk et al. [Yoruk 2006a] proposed a biometric system fusing hand shape and texture using Independent Component Analysis (ICA) features. A CIR of 97.21% is achieved for 458 subjects of Bosphorus hand database, with 2 samples of training images. On the other hand, Kumar and Zhang [Kumar 2006b] developed a bimodal biometric system combining geometrical features of the hand and discrete cosine transform (DCT) coefficients of the palmprint trait. The fusion is performed at feature level and achieves a CIR=98% for 100 subjects of UST (University of Science and Technology) hand database. Choras and Choras [Choras 2007] also presented a bimodal biometric system fusing the curvature analysis features of hand geometry and Zernike moments features of palmprint modality, at matching score level. Experiments evaluated on 100 subjects using a proprietary database obtain a CIR = 91.33% for three samples for each subject. However, Wang et al. [Wang 2009] extracted contour features of the hand shape and wavelet features from palmprint biometric trait. The fusion at feature level is based on the concatenation, after normalization step, of the two feature vectors of hand shape and palmprint modalities. The evaluation on 260 subjects of a proprietary hand database demonstrates a CIR=96.98% using 6 images for each person. Ferrer et al. [Ferrer 2011] proposed a bimodal biometric system fusing hand geometry and palmprint modalities. They performed fusion at feature level by the concatenation of feature vectors generated from geometrical features of the hand and Gaussian filter features of the palmprint. Experiments, assessed on the IITD hand database containing 240 subjects with 10 samples for each subject, revealed the efficiency of this system by achieving a CIR = 99.21%. Compared to the system of Ferrer et al. [Ferrer 2011] which uses the same database, our proposed system presents higher CIR=99.57% for 230 subjects and using only 5 samples for each subject. On the other hand, compared to the system of Yoruk et al. [Yoruk 2006a] which also employed the same database, our proposed system proves its efficiency by achieving better CIR=97.61% for 615 subjects against CIR=97.21% for 458 subjects. Our proposed system is also compared

to our previous work which extracted SIFT descriptors from hand shape and palmprint modalities and the matching step was employed to compare between training and testing images. The fusion at matching score level achieves a CIR=97.82% for IITD hand database and CIR=95.46% for Bosphorus hand database. The proposed system SSRHSPI presents better performance for these two databases compared to our previous work. Hence, it can be seen from table 6.12 the influence of SIFT sparse representation features, extracted from hand shape and palmprint modalities as well as the effect of the proposed fusion scheme, which combine feature and decision levels, compared to other analogous approaches.

TABLE 6.12: Comparison of performances between the proposed approach and other existing approaches fusing hand shape and palmprint modalities

Reference	Database	Users (images)	Method	Fusion level	CIR (%)
Yoruk et al., 2006 [Yoruk 2006a]	Bosphorus	458 (3)	ICA features	Feature	97.21
Kumar and Zhang, 2006 [Kumar 2006b]	UST	100 (10)	Geometric features +DCT coefficients	Feature	98
Choras and Choras, 2007 [Choras 2007]	Proprietary	100 (3)	Curvature analysis +Zernike moments	Score	91.33
Wang et al., 2009 [Wang 2009]	Proprietary	260 (6)	Contour features +Wavelet features	Feature	96.98
Ferrerr et al., 2011 [Ferrerr 2011]	IITD	240 (10)	Geometric features +Gaussian filter	Feature	99.21
Proposed SSRHSPI	Charfi et al., 2014 [Charfi 2014]	IITD	SIFT descriptors	Score	97.82
		Bosphorus			95.46
	Bosphorus	IITD	SIFT sparse representation	Feature + Decision	99.50
		IITD			99.57
		Bosphorus			98.50
		Bosphorus			97.61

We have also evaluated our system in terms of execution time. The proposed biometric system is implemented using Matlab 2014a on a computer with 2.5 GHz,

Intel core i3 CPU and 4GB RAM. Table 6.13 lists the execution time relative to each step and reveals that our identification system requires less than 2 seconds from one hand image for persons identification.

TABLE 6.13: Execution time

Steps	Average execution time (ms)
Preprocessing	750
Feature extraction	463
Sparse representation	667
Fusion	25
Identification	12
Total	1917

6.4 Multi-instance palmprint identification method

In this section, we present a toucheless palmprint identification method based on multi-instance fusion, combining left and right palmprints. The developed method adopts SIFT descriptors as local invariant features to extract palmprint features, that are then sparsely represented using sparse representation method. The fusion of left and right palmprints is performed at rank level using multi-class SVM classifier and probability distribution, as illustrated in figure 6.12.

6.4.1 Fusion at rank level using probability distribution

The classification using SVM method provides scores relative to each class for each image sample. These scores may be regarded as the belonging degree of each image to all classes (or persons). Our purpose is to transform these scores into probability measures. Thus, the problem may be formulated as follows: *what is the probability that the image i belongs to the person h ?*

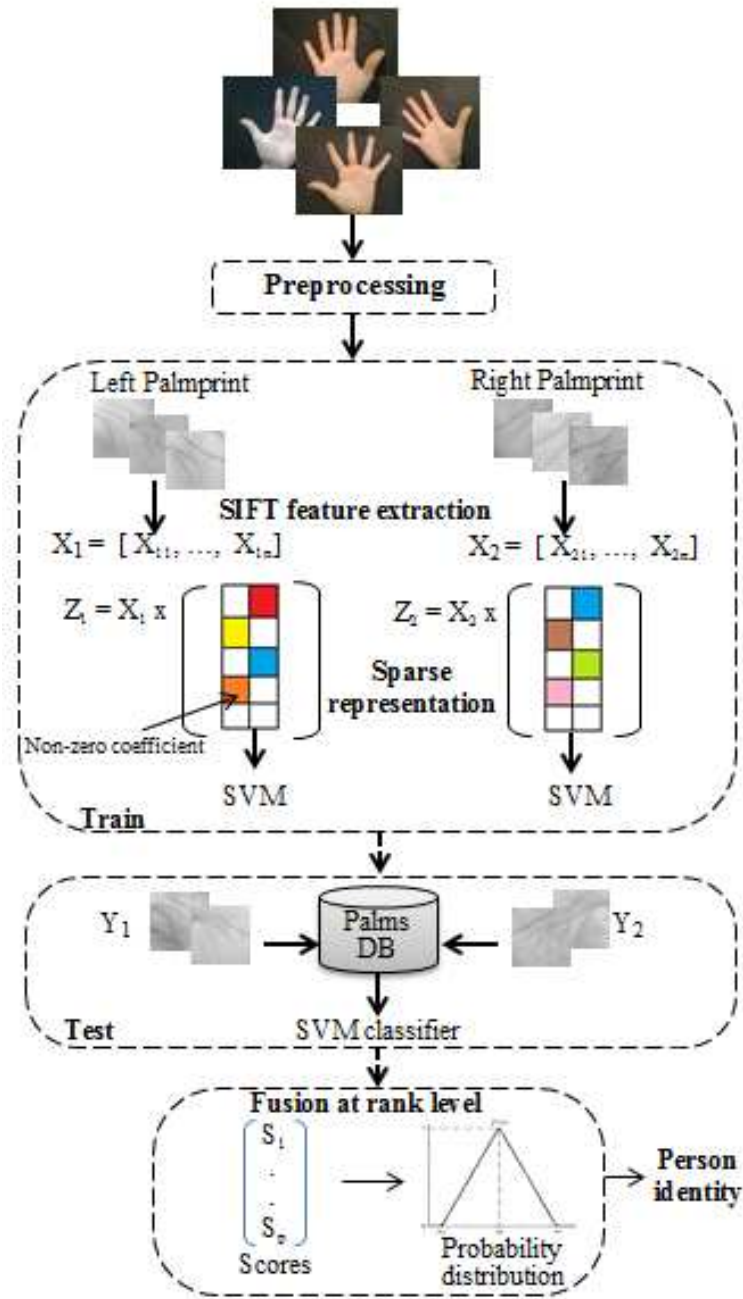


FIGURE 6.12: Flowchart of the proposed palmprint identification method.

6.4.1.1 Probability knowledge basis

To build the probability knowledge basis, scores extracted from SVM classification method should be transformed into a probability measures.

Let Ω be the space of score values as $\Omega = \{I_1, I_2, \dots, I_j, \dots, I_J\}$ where P_j is the individual number j represented by a palmprint image; and $j \in [1 \dots J]$ where

J is the number of individuals. In fact, for each image, the following steps are considered:

- A descriptor sparsely represented is employed in order to provide a feature vector.
- A classification is performed to the feature vector by generating weights or scores of its belonging to a person, as follows: $\omega[s_{i1}, s_{i2}, \dots, s_{iN}]$
- For each score s_{iN} , a probability distribution is estimated $P_{iN}(s_{iN})$ where $i \in \{1, 2, \dots, J\}$; $n \in 1, 2, \dots, N$; and Ω_{in} is the space definition of s_{in}

These steps generate the probability distributions of each score for J individuals.

6.4.1.2 Probability distributions of the scores

The probability distributions are estimated by defining a function which transforms scores into probability measures. In our work, the triangular probability distribution is applied for each score, as follows: [Guesmi 2013]

- Compute the deviation of the triangular distribution of each test image, expressed as:

$$D = \sqrt{\sum_{i=1}^m (s_i - q)^2} \quad (6.6)$$

where m is the number of persons; s_i is the value of matching score relative to each person i ($i \in [1..m]$) and $q = (\sum_{i=1}^m (s_i)/m)$.

- Establish the triangular probability distribution as follows:
 - The coordinates of upper and lower limits (a and c) of the triangular distribution are determined from the deviation and the peak location b in which the probability measure is equal to 1.
 - $(x_a^i, y_a^i) = (s_i - D, 0)$ and $(x_c^i, y_c^i) = (s_i + D, 0)$

- The probability measure 1 is assigned to the average value between x_A and x_C coordinates.
- The probability density function is given by:

$$f(x) = \begin{cases} \frac{2(x - x_a)}{(x_c - x_a)(x_b - x_a)} ; x_a \leq x \leq x_b \\ \frac{2(x_c - x)}{(x_c - x_a)(x_c - x_b)} ; x_b \leq x \leq x_c \\ 0 ; x < x_a, x > x_c \end{cases} \quad (6.7)$$

- For each test image, probability measures of $f(x)$ are stored.
- Repeat the previous steps for each test image.

Figure 6.13 represents an example of triangular probability distribution for one test image.

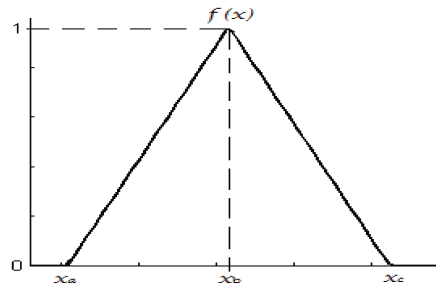


FIGURE 6.13: Example of triangular probability distribution.

The principal aim of classification task is to distinguish between different classes (or persons). Nevertheless, there exists an ambiguity between some classes which may result a mis-classification. Therefore, motivated by the work of Bounhas et al. [Bounhas 2012], the ambiguity difference is computed based on the ratio of probability measures of the second most relevant class and the first most relevant class, as follows:

$$AmbiguityRatio(t, c_1, \dots, c_n) = \frac{P(c_2|t)}{P(c_1|t)} \quad (6.8)$$

where c_1 and c_2 are, the most and the second most relevant classes, respectively, for the instance t to be classified.

The final identity decision is provided according to the *AmbiguityRatio* measured from the two palmprint instances (left and right). If the *AmbiguityRatio* measure obtained from left palmprint is higher than the *AmbiguityRatio* measure obtained from right palmprint, then the person's identity of right palmprint is considered; otherwise, the person's identity of left palmprint is considered.

6.4.2 Experimental evaluation

To assess the performance of the proposed method, an identification experiment is carried out over two databases namely the proposed REST database containing 1500 hand images and the public CASIA palmprint database containing 2400 palmprint images. Correct Identification Rate (CIR) is computed to evaluate performance of the proposed method. Table 6.14 presents CIRs obtained using left palmprints of REST hand database, for three and four training images achieving, respectively, 80.83% and 88.33%. While right palmprints achieve CIR=90.13% using three training images and CIR=93.33% using four training images. The fusion of left and right palmprints is performed at feature and rank level. Results show that the proposed fusion at rank level using probability distribution achieves better performances (CIR=97.09% using six training images and CIR=98.33% using eight training images) at rank 1 than fusion at feature level (CIR=96.38% using six training images and CIR=96.66% using eight training images). Figure 6.14 presents the CMC (Cumulative Match Characteristic) curves, which reveal that a significant performance improvement is obtained by the proposed method over each palmprint instance alone, using REST hand database, by reaching CIR=100% at rank 5 for left and right fusion.

Other experiments are performed using CASIA palmprint database. Table 6.15 demonstrates CIRs of each instance alone as well as CIRs of their fusion at rank and feature levels, using different numbers of training images. Results report that fusion of the two palmprint instances reaches 100% of CIR at the two levels, using six training images and four testing images. In the case of four training images and six testing images, fusion at feature level presents a slight increase achieving

TABLE 6.14: Correct identification rates over REST hand database

Instance	Train	Test	CIR (%)
Left palmprint	3	2	80.83
-	4	1	88.33
Right palmprint	3	2	90.13
-	4	1	93.33
Left + Right palmprints at feature level	6	4	96.38
-	8	2	96.66
Left + Right palmprints at rank level	6	4	97.09
-	8	2	98.33

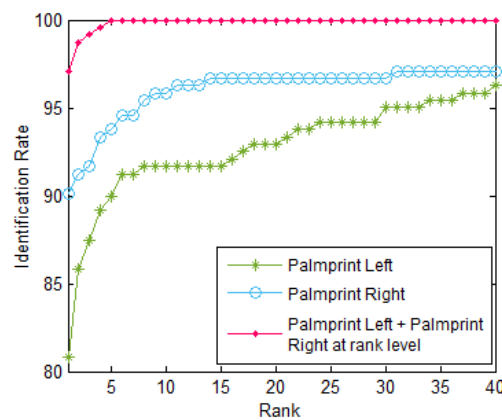


FIGURE 6.14: CMC curves of the proposed fusion method over REST hand database.

CIR=99.94% compared to CIR=99.89% of fusion at rank level. Nevertheless, fusion at rank level presents less computational cost than fusion at feature level, since less information are treated.

Table 6.16 presents a comparison between the proposed method and recent existing methods [Xu 2015, Leng 2015]. These two works have been chosen since they combine left and right palmprints over toucheless databases, as in this paper. It can be seen in table 6.16 that the proposed method is competitive by obtaining CIR=99.94% at feature level fusion, for 240 subjects, compared to the method of Leng et al. [Leng 2015], which achieves CIR=99.7% for 101 subjects at the same fusion level. Moreover, it can be pointed out that the proposed fusion method at rank level also presents better performances by achieving CIR=99.72% for 240 subjects and CIR=98.33% for 150 subjects, compared to the method of Xu et al.

TABLE 6.15: Correct identification rates over CASIA palmprint database

Instance	Train	Test	CIR (%)
Left palmprint	3	2	98.88
-	2	3	98.88
Right palmprint	3	2	97.70
-	2	3	96.52
Left + Right palmprints at feature level	6	4	100
-	4	6	99.94
Left + Right palmprints at rank level	6	4	100
-	4	6	99.89

[Xu 2015] which obtains CIR=94.64% using SIFT descriptors for 187 subjects at score level fusion, and CIR=99.57% by fusing OLOF and SIFT descriptors, for 235 subjects.

6.5 Summary and conclusion

In this chapter, different multi-types fusion for hand multimodality biometrics are presented. At first, the multi-representation hand shape verification method is developed by extracting two descriptors from the hand shape modality, namely SIFT descriptors and geometrical features. The fusion method is performed at matching score level using weighted sum rule method. The proposed multi-representation method presents some advantages. In fact, the computational complexity and the execution time of this method are not high due to the computational simplicity of the used techniques. Moreover, performances achieved are relatively promising by fusing the two descriptors (RR=97.82%). However, using a single modality (hand shape) may decrease the properties of distinctiveness and universality which are required in a biometric system. To deal with these problems, the palmprint modality is embedded and a multi-biometric fusion method based on hand shape and palmprint modalities is proposed to ameliorate verification performances. Indeed, a matching refinement process based on region and appearance of the hand trait is developed in order to remove as much as possible false matched keypoints for

TABLE 6.16: Comparison of performances between different multi-instance palmprint methods over toucheless databases

Author, year	Features	Indiv.	Fusion level	CIR(%)	
Leng et al., 2015 [Leng 2015]	Two-dimensional discrete cosine transform (2DDCT)	101	Feature level	99.7	
Xu et al., 2015 [Xu 2015]	PalmCode	187	Matching score level	99.64	
	Ordinal code	-	-	98.84	
	SIFT descriptors	-	-	94.64	
	Collaborative Representation based Classification (CRC)	-	-	99.35	
	palmCode	235	Matching score level	97.1	
	OLOF +SIFT descriptors	-	-	99.57	
Proposed method	SIFT + Sparse Representation	Sparse Multiscale Competitive Code (SMCC)	-	99.57	
		-	240	Rank level	99.72
		-	-	Feature level	99.94
		-	150	Rank level	98.33
-	-	Feature level	96.66		

each modality apart. The fusion is performed at decision level and finger surfaces trait are integrated in the case of dissimilarity between hand shape and palmprint modalities. Experiments show that this multi-biometric verification method is efficient and offers high verification rates (RR=99.82%), which are competitive to other popular multimodal approaches. Nevertheless, in the case of the identification mode, more execution time is required, since a comparison with all training images stored in database is demanded. To overcome this problem, a multi-biometric method for persons identification is proposed. In fact, SIFT descriptors are extracted from each detected keypoint from hand shape and palmprint modalities. Moreover, sparse representation based on extracted SIFT descriptors is adopted in order to represent these two biometric modalities for further classification step. A cascade fusion scheme based on feature and decision levels is proposed in order to provide the final decision about the identity of the person. This method is evaluated using two public hand databases. Experiments show promising identification rates (RR=99.57%), in less execution time, with a small number of training images and large population size. To extend our proposed identification method, a multi-instance biometric system is proposed by combining left and right palmprint features, based on SIFT sparse representation features. The fusion scheme is performed at rank level using multi-class SVM classifier and probability distribution, to generate the final identity of the person. Moreover, this system is evaluated using a new proposed toucheless hand database named REST hand database and the public CASIA palmprint database. Experiments reveal that the proposed identification method is efficient and promising identification rates are achieved for REST hand database (IR=98.33%) and CASIA palmprint database (IR=100%).

Table 6.17 presents a summary of comparisons between the different multi-type systems proposed in this thesis.

TABLE 6.17: Comparison between the different proposed multi-types

Multi-type	Mode	Modality	Features	Database	Fusion level	Performances (%)
Multi-representation method	Verification	Hand shape	-SIFT descriptors -Geometrical features	Bosphorus DB	Score	RR=97.82
Multi-biometric method	Verification	-Hand shape -Palmprint -Fingers	-SIFT descriptors -SIFT descriptors -Gabor filters	IITD DB	Decision	RR=99.82
Multi-biometric method	Identification	-Hand shape -Palmprint	SIFT sparse representation	-IITD DB -Bosphorus DB	Feature + Decision -Rank	-IR=99.57 -IR=97.61 -IR=99.72
Multi-instance method	Identification	Palmprint left/right	SIFT sparse representation	-CASIA DB -REST DB	-Feature -Rank -Feature	-IR=99.94 -IR=98.33 -IR=96.66

Chapter 7

Conclusions and future work

Biometrics is an alternative that is based on the identification of persons relying on their physical characteristics (iris, fingerprint, hand shape, etc.) and / or behavioral (voice, dynamic signature, walking, etc.). Biometrics seeks to achieve two important goals in our life. The first goal is to achieve security by eliminating doubt on the identity of a person. The second purpose is to facilitate the identification of individuals. Nowadays, this method of identification is preferred over traditional methods involving passwords and badges for different reasons: (i) the person identified must be physically present at the time of identification; (ii) the biometric techniques eliminate the need to remember a password or carry a badge.

Biometric systems which are based on a single modality are called unimodal biometric systems. Although some of these systems have achieved significant improvements in terms of reliability and accuracy, they suffer from some limitations that prevent them from being used in the recent applications. These limitations may take shape in several problems because of noisy data, intra-class variation, inter-class similarities, fraud attacks, non-universality and other factors. To overcome some of these limitations and increase the security level, the fusion of data presented by different modalities may increase the identification accuracy of the identity. This is called multimodal biometric systems.

To invest in the multi-biometric field and to achieve a robust recognition solution, we have focused, throughout this thesis, on new multimodal biometric methods in the hand biometric field based on two biometric modalities which are hand shape and palmprint traits. These two modalities have the merit of being acquired simultaneously from the hand image.

In the first part, the general context of biometry is presented by describing the properties of different biometric modalities, the structure of a general biometric system and the concept of multimodality by summarizing the different architectures of multimodal systems as well as fusion levels. In addition, we justified the choice of hand modality treated in this thesis and the principal challenges regarding the hand biometric trait. On the other hand, an overview of hand shape and palmprint modalities is put forward and different existing approaches are discussed. Moreover, multimodal hand shape and palmprint biometrics are described and a comparison between different fusion approaches is outlined.

The second part of this thesis concerns the main contributions suggested in this work. Our first contribution consists of the proposition of a new hand shape verification system. In fact, this system is based firstly on the detection of the best set of keypoints localized in the contour of the hand for further SIFT description and matching process. Secondly, a matching refinement-hand region and appearance are proposed in order to refine as much as possible mismatched keypoints. Actually, our matching refinement process is based on two levels. The first one pertains to the matching based-region refinement in which matched keypoints that are belonging to different hand regions are removed. The second one concerns matching based-appearance refinement in which the two patches relative to the two matched keypoints are represented by Gabor filters for similarity comparison. The two keypoints are removed if the similarity measure between their patches is lower than a certain threshold. The proposed hand shape verification system has proven its efficiency and robustness by achieving promising performances.

Our second contribution incorporates the proposition of a new palmprint identification system. Indeed, SIFT sparse representation method is adopted in order to describe the palmprint biometric trait. It is based chiefly on the extraction

of SIFT descriptors from each detected keypoints. Then, sparse representation based on extracted SIFT descriptors is employed so as to represent palmprint features. The proposed palmprint identification system has proven its efficiency by obtaining promising performances that are competitor to other existing palmprint recognition approaches.

Our third contribution copes with the proposed hand multi-types fusion methods for multimodality, including multi-representation fusion, multi-biometric fusion and multi-instance fusion. In fact, the multi-representation fusion is based on the combination of SIFT descriptors and geometrical features of the hand at matching score level, for hand shape verification. The multi-biometrics fusion is grounded on the combination of two biometric modalities which are the hand shape and the palmprint traits. The fusion is performed at two levels namely feature and decision levels. However, the multi-instance fusion is based on the combination of left and right palmprints and performed at rank level using probability distribution. These different fusion methods have proven their efficiency and robustness for different biometric systems by achieving promising performances which are competitive to other existing multimodal hand fusion approaches.

In the literature, the fusion methods in hand biometric field have usually been performed at feature or score level, in order to ameliorate recognition performances. However, in our work, the fusion at feature and decision levels is combined so as to generate the final identity of the person. Moreover, a fusion at rank level is performed, combining left and right palmprints. Indeed, the fusion at rank level was rarely used in the hand biometric field. For multimodal systems, the used databases were usually acquired either with direct contact or in a particular environment (indoor). Besides, the left and right hands are sometimes not appropriate to the same person. Thus, our work has the credit to create a new real touchless hand database named "REgim Sfax Tunisia hand database" composed of left and right hands and palmprints captured in free positions, without any lighting conditions or restriction of pegs.

The promising results achieved motivate us to enhance our works in these research areas as future works. Actually, a falsification attempt may occur. Accordingly,

an impostor may present to the acquisition device a picture of the hand of an authentic person. To overcome this problem, our methodology can be extended to 3D hand images. On the other hand, this problem may be resolved by integrating hand or palm veins which makes it difficult to display just a mere picture to be identified. Moreover, the proposed multi-instance method may be extended by fusing left and right hand shapes at rank level. Indeed, the probability distribution method has proven its efficiency and robustness using left and right palmprints for person identification.

Bibliography

- [Adan 2008] M. Adan, A. Adan, A.S. Vezquez and R. Torres. *Biometric verification/identification based on hands natural layout*. Image and Vision Computing, vol. 26, no. 4, pages 451 – 465, 2008.
- [Aharon 2006] M. Aharon, M. Elad and A. Bruckstein. *K -SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation*. IEEE Transactions on Signal Processing, vol. 54, no. 11, pages 4311–4322, Nov 2006.
- [Amayeh 2006] G. Amayeh, G. Bebis, A. Erol and M. Nicolescu. *Peg-Free Hand Shape Verification Using High Order Zernike Moments*. In Proceedings of the 2006 Conference on Computer Vision and Pattern Recognition Workshop, pages 40–47, 2006.
- [Amayeh 2009] G. Amayeh, G. Bebis, A. Erol and M. Nicolescu. *Hand-based verification and identification using palm-finger segmentation and fusion*. Computer Vision and Image Understanding, vol. 113, no. 4, pages 477 – 501, 2009.
- [Asish 2015] B. Asish, B. Debotosh and N. Mita. *Fusion-Based Hand Geometry Recognition Using Dempster-Shafer Theory*. International Journal of Pattern Recognition and Artificial Intelligence, vol. 29, 2015.
- [Bo 2013] L. Bo, X. Ren and D. Fox. *Multipath Sparse Coding Using Hierarchical Matching Pursuit*. pages 660–667, June 2013.

- [Boucetta 2013] A. Boucetta and K.E. Melkemi. *Hand Shape Recognition Using Hu and Legendre Moments*. In Proceedings of the 6th International Conference on Security of Information and Networks, SIN '13, pages 272–276, 2013.
- [Bounhas 2012] M. Bounhas, K. Mellouli, H. Prade and M. Serrurier. *Possibilistic classifiers for numerical data*. Soft Computing, vol. 17, no. 5, pages 733–751, 2012.
- [Briceno 2011] J.C. Briceno, C.M. Travieso, J.B. Alonso and M.A. Ferrer. *Biometric Identification Based on Hand-shape features using a HMM Kernel*. In Hand-Based Biometrics (ICHB), 2011 International Conference on, pages 1–6. IEEE, 2011.
- [Buddharaju 2007] P. Buddharaju, I.T Pavlidis, P. Tsiamyrtzis and M. Bazakos. *Physiology-Based Face Recognition in the Thermal Infrared Spectrum*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 4, pages 613–626, 2007.
- [Chakraborty 2013] S. Chakraborty, I. Bhattacharya and A. Chatterjee. *A palm-print based biometric authentication system using dual tree complex wavelet transform*. Measurement, vol. 46, no. 10, pages 4179 – 4188, 2013.
- [Charfi 2014] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Bimodal biometric system based on SIFT descriptors of hand images*. 2014 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2014, USA, October 5-8, 2014, pages 4141–4145, 2014.
- [Charfi 2015a] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Hand verification system based on multi-features fusion*. In 15th International Conference on Intelligent Systems Design and Applications (ISDA2015), pages 189–194, 2015.
- [Charfi 2015b] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Personal Recognition System using Hand Modality based on Local Features*. In

- 11th International Conference on Information Assurance and Security (IAS2015), pages 13–17, 2015.
- [Charfi 2016a] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Bimodal biometric system for hand shape and palmprint recognition based on SIFT sparse representation*. Multimedia Tools and Applications, pages 1–26, 2016.
- [Charfi 2016b] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Local invariant representation for multi-instance toucheless palmprint identification*. In International conference on Systems, Man and Cybernetics (SMC2016), 2016.
- [Charfi 2016c] N. Charfi, H. Trichili, A.M. Alimi and B. Solaiman. *Personal verification system using hand modalities*. In International Journal on Information Assurance and Security (JIAS), volume 11, pages 157–168, 2016.
- [Chen 2001] S.S. Chen, D.L. Donoho and M.A. Saunders. *Atomic Decomposition by Basis Pursuit*. Society for Industrial and Applied Mathematics, vol. 43, no. 1, pages 129–159, January 2001.
- [Chen 2008] J. Chen and Y.S. Moon. *Using SIFT features in palmprint authentication*. Pattern Recognition, 2008. ICPR 2008. 19th International Conference on, pages 1–4, Dec 2008.
- [Choras 2007] R.S. Choras and M. Choras. *Adaptive and Natural Computing Algorithms: 8th International Conference, ICANNGA 2007, Warsaw, Poland, April 11-14, 2007, Proceedings, Part II*. pages 407–414, 2007.
- [Cootes 1992] T.F. Cootes and C.J. Taylor. *Active Shape Models - Smart Snakes*. In in Proceedings of the British Machine Vision Conference, 1992.
- [Cootes 1995] T.F. Cootes, C.J. Taylor, D.H. Cooper and J. Graham. *Active Shape Models—Their Training and Application*. Computer Vision and Image Understanding, vol. 61, no. 1, pages 38–59, January 1995.

- [Cootes 1998] T.F. Cootes, G.J. Edwards and C.J. Taylor. *Active Appearance Models*. In IEEE Transactions on Pattern Analysis and Machine Intelligence, pages 484–498. Springer, 1998.
- [D’Ornellas 2006] M.C. D’Ornellas. *A deformable contour based approach to hand image segmentation*. International Journal of Forensic Computer Science, vol. 1, pages 10–18, 2006.
- [Dutagaci 2006] H. Dutagaci, B. Sankur and E. Yoruk. *Comparative analysis of global hand appearance-based person recognition*. Journal of Electronic Imaging, pages 011018–1 – 011018–19, 2006.
- [Dutagaci 2008] H. Dutagaci, B. Sankur and E. Yoruk. *A comparative analysis of global hand appearance-based person recognition*. Journal Electronic Imaging, pages 011018/1– 011018/19, 2008.
- [Ernst 1971] R.H. Ernst. *Hand ID system*. U. S. Patent No. 3576537, 1971.
- [Ferrer 2007] M.A. Ferrer, A. Morales, C.M. Travieso and J.B. Alonso. *Low Cost Multimodal Biometric identification System Based on Hand Geometry, Palm and Finger Print Texture*. In Security Technology, 2007 41st Annual IEEE International Carnahan Conference on, pages 52–58, 2007.
- [Ferrer 2011] M.A. Ferrer, F. Vargas and A. Morales. *BiSpectral contactless hand based biometric system*. Telecommunications (CONATEL), 2011 2nd National Conference on, pages 1–6, May 2011.
- [Fouquier 2007] G. Fouquier, L. Likforman, J. Darbon and B. Sankur. *The Biosecure Geometry-Based System for Hand Modality*. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2007), vol. 1, pages I–801–I–804, April 2007.
- [Ghandehari 2012] A. Ghandehari, M. Anvaripour and S. Soltanpour. *Palmprint verification and identification using pyramidal HOG feature and fast tree based matching*. In 5th IAPR International Conference on Biometrics (ICB), pages 421–426, 2012.

- [Ghoualmi 2015] L. Ghoualmi, S. Chikhi and A. Draa. *A SIFT-Based Feature Level Fusion of Iris and Ear Biometrics*. pages 102–112, 2015.
- [Goh 2012] M.K.O. Goh, C. Tee and A.B.J. Teoh. *A Contactless Biometric System using Multiple Hand Features*. Journal of Visual Communication and Image Representation (JVIS), Elsevier, pages 1068–1084, 2012.
- [Golfarelli 1997] M. Golfarelli, D. Maio and D. Malton. *On the error-reject trade-off in biometric verification systems*. Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 19, no. 7, pages 786–796, Jul 1997.
- [Gross 2007] R. Gross, Y. Li, L. Sweeney, X. Jiang, W. Xu and D. Yurovsky. *Robust Hand Geometry Measurements for Person Identification using Active Appearance Models*. In First IEEE International Conference on Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007., pages 1–6, 2007.
- [Guesmi 2013] H. Guesmi, H. Trichili, A. M. Alimi and B. Solaiman. *Fingerprint verification system based on curvelet transform and possibility theory*. Multimedia Tools and Applications, pages 3253–3272, 2013.
- [Guo 2012] J.M. Guo, C.H. Hsia, Y.F. Liu, J.C. Yu, M.H. Chu and T.N. Le. *Contact-free Hand Geometry-based Identification System*. Expert Systems with Applications, vol. 39, no. 14, pages 11728–11736, October 2012.
- [Guo 2014] X. Guo, W. Zhou and Y. Wang. *Palmprint recognition algorithm with horizontally expanded blanket dimension*. Neurocomputing, vol. 127, pages 152 – 160, 2014.
- [Haghighat 2013] M. Haghighat, S. Zonouz and M. Abdel-Mottaleb. *Identification Using Encrypted Biometrics*. Computer Analysis of Images and Patterns, vol. 8048, pages 440–448, 2013.
- [Hameed 2012] M.A. Hameed. *Comparative Analysis of Orthogonal Matching Pursuit and Least Angle Regression*. MS Thesis, Michigan State University, vol. 36, 2012.

- [Hammami 2014] M. Hammami, S. Ben Jemaa and H. Ben-Abdallah. *Selection of discriminative sub-regions for palmprint recognition*. Multimedia Tools and Applications, vol. 68, no. 3, pages 1023–1050, 2014.
- [Ho 1994] T.K. Ho, J.J. Hull and S.N. Srihari. *Decision combination in multiple classifier systems*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 16, no. 1, pages 66–75, Jan 1994.
- [Hong 2016] D. Hong, W. Liu, X. Wu, Z. Pan and J. Su. *Robust palmprint recognition based on the fast variation Vese-Osher model*. Neurocomputing, vol. 174, Part B, pages 999–1012, 2016.
- [Hu 2012] R.X. Hu, W. Jia, D. Zhang, J. Gui and L.T. Song. *Hand shape recognition based on coherent distance shape contexts*. Pattern Recognition, vol. 45, no. 9, pages 3348 – 3359, 2012.
- [Huang 1995] Y.S. Huang and C.Y. Suen. *A method of combining multiple experts for the recognition of unconstrained handwritten numerals*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 17, no. 1, pages 90–94, Jan 1995.
- [Jain 1999a] A.K. Jain and N. Duta. *Deformable Matching of Hand Shapes for User Verification*. Proc. Int. Conference Image Processing, pages 857–861, 1999.
- [Jain 1999b] A.K. Jain, A. Ross and S. Pankanti. *A Prototype Hand Geometry-based Verification System*. 2nd Int Conference on Audio and Video-based Biometric Person Authentication (AVBPA), pages 166–171, 1999.
- [Jain 2004] A.K. Jain, A. Ross and S. Prabhakar. *An introduction to biometric recognition*. IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, pages 4–20, 2004.
- [Jain 2007] A.K. Jain. *Technology: Biometric recognition*. In International journal of Science, pages 38–40, 2007.

- [Jain 2009] A.K. Jain and J. Feng. *Latent Palmprint Matching*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 31, no. 6, pages 1032–1047, June 2009.
- [Jia 2008] W. Jia, D.S. Huang and D. Zhang. *Palmprint verification based on robust line orientation code*. Pattern Recognition, vol. 41, no. 5, pages 1504 – 1513, 2008.
- [Jing 2013] L. Jing, C. Jian and L. Kaixuan. *Improve the two-phase test samples representation method for palmprint recognition*. Optik - International Journal for Light and Electron Optics, vol. 124, no. 24, pages 6651 – 6656, 2013.
- [Kang 2014] W. Kang and Q. Wu. *Pose-Invariant Hand Shape Recognition Based on Finger Geometry*. IEEE Systems, Man and Cybernetics (SMC), 2014.
- [Kass 1988] M. Kass, A. Witkin and D. Terzopoulos. *Snakes: Active contour models*. International journal of Computer Vision, vol. 1, no. 4, pages 321–331, 1988.
- [Keren 1994] D. Keren. *Using symbolic computation to find algebraic invariants*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 16, no. 11, pages 1143–1149, Nov 1994.
- [Kong 2004] A.W.K. Kong and D. Zhang. *Competitive coding scheme for palmprint verification*. 17th International Conference on Pattern Recognition (ICPR), page 520–523, 2004.
- [Kong 2009] A. Kong, D. Zhang and M. Kamel. *A survey of palmprint recognition*. Pattern Recognition, vol. 42, no. 7, pages 1408 – 1418, 2009.
- [Kukula 2006] E. Kukula and S. Elliott. *Implementation of hand geometry: an analysis of user perspectives and system performance*. IEEE Aerospace and Electronic System Magazine, vol. 21, pages 3 – 9, 2006.
- [Kumar 2003] A. Kumar, D.C.M. Wong, H.C. Shen and A.K. Jain. *Personal Verification Using Palmprint and Hand Geometry Biometric*. 4th International

- Conference on Audio- and Video-based Biometric Person Authentication, pages 668–678, 2003.
- [Kumar 2006a] A. Kumar, D.C.M. Wong, H.C. Shen and A.K. Jain. *Personal authentication using hand images*. Pattern Recognition Letters, vol. 27, no. 13, pages 1478 – 1486, 2006.
- [Kumar 2006b] A. Kumar and D. Zhang. *Personal recognition using hand shape and texture*. IEEE Transactions on Image Processing, vol. 15, no. 8, pages 2454–2461, Aug 2006.
- [Kumar 2008] A. Kumar. *Incorporating Cohort Information for Reliable Palm-print Authentication*. 6th Indian Conference on Computer Vision, Graphics Image Processing, ICVGIP '08., pages 583–590, Dec 2008.
- [Kumar 2009] A. Kumar, T.S. Mundra and A. Kumar. *Anatomy of Hand*. Encyclopedia of Biometrics. New York: Springer, 2009.
- [Kumar 2011a] A. Kumar and S. Shekhar. *Personal Identification Using Multi-biometrics Rank-Level Fusion*. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, vol. 41, no. 5, pages 743–752, Sept 2011.
- [Kumar 2011b] A. Kumar and S. Shekhar. *Personal Identification Using Multi-biometrics Rank-Level Fusion*. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, vol. 41, no. 5, pages 743–752, 2011.
- [Kuncheva 2004] L.I. Kuncheva. *Combining pattern classifiers: Methods and algorithms*. Wiley-Interscience, 2004.
- [Lam 1997] L. Lam and S.Y. Suen. *Application of majority voting to pattern recognition: an analysis of its behavior and performance*. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 27, no. 5, pages 553–568, Sep 1997.

- [Lamard 2010] L. Lamard, A. Histace and B. Matuszewski. *Contours actifs paramétriques fondés sur le calcul de distances inter histogrammes pour la segmentation d'images médicales*. In CNRIUT, 2010.
- [Lee 2007] H. Lee, A. Battle, R. Raina and A.Y. Ng. *Efficient sparse coding algorithms*. pages 801–808, 2007.
- [Leng 2015] L. Leng, M. Li, C. Kim and X. Bi. *Dual-source discrimination power analysis for multi-instance contactless palmprint recognition*. Multimedia Tools and Applications, pages 1–22, 2015.
- [Liliana 2012] D.Y. Liliana and E.T. Utaminingsih. *The combination of palm print and hand geometry for biometrics palm recognition*. International Journal of Video and Image Processing and Network Security, vol. 12, pages 1 – 5, 2012.
- [Lowe 1999] D.G. Lowe. *Object Recognition from Local Scale-Invariant Features*. In Proceedings of the International Conference on Computer Vision, volume 2 of *ICCV '99*, pages 1150–, Washington, DC, USA, 1999. IEEE Computer Society.
- [Lowe 2004] D.G. Lowe. *Distinctive image features from scale-invariant keypoints*. International journal of computer vision, vol. 60, no. 2, pages 91–110, 2004.
- [Lu 2003] G. Lu, D. Zhang and K. Wang. *Palmprint recognition using eigenpalms features*. Pattern Recognition Letters, vol. 24, pages 1463 – 1467, 2003.
- [Luo 2016] Y.T. Luo, L.Y. Zhao, B. Zhang, W. Jia, F. Xue, J.T. Lu, Y.H. Zhu and B.Q. Xu. *Local line directional pattern for palmprint recognition*. Pattern Recognition, vol. 50, pages 26–44, 2016.
- [Luque-Baena 2013] R.F. Luque-Baena, D. Elizondo, E. Lopez-Rubio, E.J. Palomo and T. Watson. *Assessment of geometric features for individual identification and verification in biometric hand systems*. Expert Systems with Applications, vol. 40, no. 9, pages 3580–3594, 2013.

- [Malik 2011] J. Malik, R. Dahiya and G. Sainarayanan. *Fast Complex Gabor Wavelet Based Palmprint Authentication*. International Journal of Image Processing, vol. 5, pages 283–297, 2011.
- [Meshgini 2013] S. Meshgini, A. Aghagolzadeh and H. Seyedarabi. *Face recognition using Gabor-based direct linear discriminant analysis and support vector machine*. Computers and Electrical Engineering, vol. 39, pages 727–745, 2013.
- [Missaoui 2005] R. Missaoui, M. Sarifuddin, N. Baaziz and V. Guesdon. *Detection efficace de contours par decomposition de l'image en regions homogenes*. 3rd International Conference: Sciences of Electronic, Technologies of Information and Telecommunications SETIT'05, Sousse, Tunisia, 2005.
- [Morales 2008] A. Morales, M.A. Ferrer, F. Diaz, J.B. Alonso and C.M. Travieso. *Contact-free hand biometric system for real environments*. 16th European Conference of Signal Processing, pages 1–5, Aug 2008.
- [Morales 2011] A. Morales, M.A. Ferrer and A. Kumar. *Towards contactless palmprint authentication*. Computer Vision, IET, vol. 5, no. 6, pages 407–416, 2011.
- [Oden 2003] C. Oden, A. Ercil and B. Buke. *Combining Implicit Polynomials and Geometric Features for Hand Recognition*. Pattern Recognition Letters, vol. 24, no. 13, pages 2145–2152, 2003.
- [Panigrahy 2008] S.K. Panigrahy, D. Jena and S.K. Jena. *A Rotational-and Translational-Invariant Palmprint Recognition System*. First International Conference on Data Engineering and Management, pages 380–383, 2008.
- [Park 2013] G. Park and S. Kim. *Hand Biometric Recognition Based on Fused Hand Geometry and Vascular Patterns*. Sensors, vol. 13, no. 3, pages 2895–2910, 2013.

- [Pati 1993] Y.C. Pati, R. Rezaifar and P.S. Krishnaprasad. *Orthogonal matching pursuit: recursive function approximation with applications to wavelet decomposition*. vol. 1, pages 40–44, Nov 1993.
- [Pavesic 2004] N. Pavesic, S. Ribaric and D. Ribaric. *Personal authentication using hand-geometry and Palmprint features*. Workshop on Biometrics at ICPR'04, Cambridge, 2004.
- [Prasad 2009] S.M. Prasad, V.K. Govindan and P.S. Sathidevi. *Bimodal Personal Recognition Using Hand Images*. International Conference on Advances in Computing, Communication and Control, pages 403–409, 2009.
- [Ribaric 2005] S. Ribaric and I. Fratric. *A biometric identification system based on eigenpalm and eigenfinger features*. IEEE Transactions on Pattern Analysis and Machine Intelligence, pages 1698–1709, 2005.
- [Ross 2007] A. Ross. *An introduction to multibiometrics*. In Signal Processing Conference, 2007 15th European, pages 20–24, Sept 2007.
- [Sanchez-Reillo 2000] R. Sanchez-Reillo, C. Sanchez-Avila and A. Gonzalez-Marcos. *Biometric Identification Through Hand Geometry Measurements*. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 10, pages 1168–1171, October 2000.
- [Saranli 2001] A. Saranli and M. Demirekler. *A statistical unified framework for rank-based multiple classifier decision combination*. Pattern Recognition, vol. 34, no. 4, pages 865–884, 2001.
- [Sharma 2015] S. Sharma, S.R. Dubey, S.K. Singh, R. Saxena and R.K. Singh. *Identity verification using shape and geometry of human hands*. Expert Systems with Applications, vol. 42, no. 2, pages 821 – 832, 2015.
- [Shen 2007] L. Shen, L. Bai and M. Fairhurst. *Gabor wavelets and General Discriminant Analysis for face identification and verification*. Image and Vision Computing, vol. 25, no. 5, pages 553 – 563, 2007.

- [Shu 1998] W. Shu and D. Zhang. *Palmprint verification: an implementation of biometric technology*. 14th International Conference on Pattern Recognition, vol. 1, pages 219–221, 1998.
- [Si 2010] Z. Si and Y.N. Wu. *Wavelet, Active Basis, and Shape Script: A Tour in the Sparse Land*. International Conference on Multimedia Information Retrieval, pages 201–210, 2010.
- [Sidlauskas 1988] D.P. Sidlauskas. *3D hand profile identification apparatus*. US. Patent no. 473620, 1988.
- [Sidlauskas 1994] D.P. Sidlauskas. *HAND: give me five*. IEEE Spectrum, pages 24–25, 1994.
- [Soille 2003] P. Soille. *Morphological Image Analysis: Principles and Applications*. Book in Springer-Verlag publisher, 2003.
- [Srinivas 2009] B.G. Srinivas and P. Gupta. *Palmprint Based Verification System Using SURF Features*. Communications in Computer and Information Science, vol. 40, pages 250–262, 2009.
- [Sun 2005] Z. Sun, T. Tan, Y. Wang and S.Z. Li. *Ordinal palmprint representation for personal identification*. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR’05), volume 1, pages 279–284, 2005.
- [Teng 2005] X. Teng, Y. Liu and C. Liu. *AAM Based Matching of Hand Appearance for User Verification*. 5th Chinese Conference on Biometric Recognition, SINOBIOMETRICS, pages 690–695, 2005.
- [Tibshirani 1994] R. Tibshirani. *Regression Shrinkage and Selection Via the Lasso*. Journal of the Royal Statistical Society, Series B, vol. 58, pages 267–288, 1994.
- [Tiwari 2013] K. Tiwari, D.K. Arya, G.S. Badrinath and P. Gupta. *Designing palmprint based recognition system using local structure tensor and force field transformation for human identification*. Neurocomputing, vol. 116, pages 222 – 230, 2013.

- [Vedaldi] A. Vedaldi. *An implementation of Lowe's Scale Invariant Feature Transform*.
- [Wang 2009] W.C. Wang, W.S. Chen and S.W. Shih. *Biometric Recognition by Fusing Palmprint and Hand-geometry Based on Morphology*. IEEE International Conference on Acoustics, Speech and Signal Processing, pages 893–896, 2009.
- [Wang 2012] X. Wang, L. Lei and M. Wang. *Palmprint verification based on 2D-Gabor wavelet and pulse-coupled neural network*. Knowledge-Based Systems, vol. 27, pages 451–455, 2012.
- [Wayman 2001] L.J. Wayman. *Fundamentals of Biometric Authentication Technologies*. International Journal of Image and Graphics, vol. 1, no. 01, pages 93–113, 2001.
- [Wu 2006] X. Wu, D. Zhang and K. Wang. *Palm line extraction and matching for personal authentication*. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 36, no. 5, pages 978–987, Sept 2006.
- [Wu 2015] X. Wu and Q. Zhao. *Deformed Palmprint Matching Based on Stable Regions*. IEEE Transactions on Image Processing, vol. 24, no. 12, pages 4978–4989, 2015.
- [Xiong 2005] W. Xiong, K.A. Toh, W.Y. Yau and X. Jiang. *Model-guided deformable hand shape recognition without positioning aids*. Pattern Recognition, vol. 38, no. 10, pages 1651–1664, 2005.
- [Xu 1992] L. Xu, A. Krzyzak and C.Y. Suen. *Methods of combining multiple classifiers and their applications to handwriting recognition*. IEEE Transactions on Systems, Man, and Cybernetics, vol. 22, no. 3, pages 418–435, May 1992.

- [Xu 2015] Y. Xu, L. Fei and D. Zhang. *Combining Left and Right Palmprint Images for More Accurate Personal Identification*. IEEE Transactions on Image Processing, vol. 24, pages 549–559, 2015.
- [Yang 2009] J. Yang, K. Yu, Y. Gong and T. Huang. *Linear spatial pyramid matching using sparse coding for image classification*. In IEEE Conference on Computer Vision and Pattern Recognition(CVPR), 2009.
- [Yoruk 2006a] E. Yoruk, H. Dutagaci and B. Sankur. *Hand biometrics*. Image and Vision Computing, vol. 24, no. 5, pages 483–497, 2006.
- [Yoruk 2006b] E. Yoruk, E. Konukoglu, B. Sankur and J. Darbon. *Shape-based hand recognition*. Image Processing, IEEE Transactions on, vol. 15, no. 7, pages 1803–1815, 2006.
- [Yuan 2006] Y. Yuan and K. Barner. *An Active Shape Model Based Tactile Hand Shape Recognition with Support Vector Machines*. In 40th Annual Conference on Information Sciences and Systems, pages 1611–1616, 2006.
- [Yuan 2011] W. Yuan and L. Jing. *Hand-Shape Feature Selection and Recognition Performance Analysis*. International Conference on Hand-Based Biometrics (ICHB), pages 1–6, 2011.
- [Yue 2014] F. Yue and W. Zuo. *Consistency analysis on orientation features for fast and accurate palmprint identification*. Information Sciences, vol. 268, pages 78 – 90, 2014.
- [Zhang 2010] D. Zhang, Z. Guo, G. Lu, L. Zhang and W. Zuo. *An Online System of Multispectral Palmprint Verification*. IEEE Transactions on Instrumentation and Measurement, vol. 59, no. 2, pages 480–490, Feb 2010.
- [Zuo 2010] W. Zuo, Z. Lin, Z. Guo and D. Zhang. *The multiscale competitive code via sparse representation for palmprint verification*. In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2265–2272, 2010.

List of publications

- **Published papers in international journals:**

1. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Bimodal biometric system for hand shape and palmprint recognition based on SIFT sparse representation", in Multimedia Tools and Applications (MTAP), issn:1573-7721, vol. 76, pp. 20457–20482, 2017.

2. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Personal verification system using hand modalities", Journal of Information Assurance and Security (JIAS), issn:1554-1010, vol. 11, no. 3, pp. 157–168, 2016.

- **Published papers in international conferences:**

3. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Local invariant representation for multi-instance toucheless palmprint identification", International conference on Systems, Man and Cybernetics (SMC), 2016.

4. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Hand verification system based on multi-features fusion", 15th International conference on Intelligent Systems Design and Applications (ISDA), pp. 189-194, 2015.

5. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Personal recognition system using hand modality based on local features",

11th International conference on Information Assurance and Security (IAS), pp. 13-17, 2015.

6. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Novel hand biometric system using invariant descriptors", 6th International Conference on Soft Computing and Pattern Recognition (SoCPaR), pp. 261-266, 2014.

7. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Bimodal biometric system based on SIFT descriptors of hand images", International conference on Systems, Man and Cybernetics (SMC), pp. 4141-4145, 2014.

8. **Nesrine Charfi**, Hanene Trichili, Adel M. Alimi and Basel Solaiman, "Etude comparative de quelques méthodes biométriques basées sur la biométrie de la forme de la main", 9ème édition des ateliers de travail sur le traitement et l'analyse de l'information (TAIMA), Mai 13-18, 2013.

La biométrie est une alternative qui se base sur l'identification des personnes à partir de leurs caractéristiques physiques (empreinte digitale, forme de la main, empreinte palmaire) et/ou comportementales (voix, signature dynamique). La biométrie tend à réaliser deux buts importants dans notre vie courante. Le premier but est de réaliser la sécurité en éliminant le doute sur l'identité d'une personne et le second but est de faciliter l'identification des individus. En effet, cette méthode d'identification est de plus en plus préférée par rapport aux méthodes traditionnelles impliquant les mots de passe et les badges. Les travaux de recherche de cette thèse s'inscrivent dans le cadre de la reconnaissance de personnes à l'aide de la biométrie de la main. L'objectif principal est de concevoir un système biométrique multimodal basé sur la fusion de la forme de la main et de l'empreinte palmaire.

La première partie de cette thèse propose un nouveau système unimodal de vérification de la forme de la main. En effet, ce système est basé d'une part, sur la détection du meilleur ensemble des points-clés localisés sur le contour de la main pour adopter la description SIFT (Scale Invariant Feature Transform). D'autre part, un raffinement de correspondance, basé région et apparence de la main est proposé, afin de raffiner autant que possible les points-clés faussement matchés.

Tandis que la deuxième partie consiste à proposer un nouveau système d'identification palmaire. En effet, la méthode de représentation parcimonieuse est adoptée afin de décrire le trait biométrique de l'empreinte palmaire. Elle est basée sur l'extraction de descripteurs SIFT de chacun des points-clés détectés.

Notre troisième partie concerne la proposition de différentes méthodes de fusion multi-types de la multi modalité, comprenant la fusion multi-représentation, la fusion multi-biométrique et la fusion multi-instance. En effet, la fusion multi-représentation est basée sur la combinaison de descripteurs SIFT et les caractéristiques géométriques de la main au niveau des scores, pour la vérification de la forme de la main. La fusion multi-biométrique est basée sur la combinaison des deux modalités biométriques à savoir la forme de la main et l'empreinte palmaire, au niveau des caractéristiques et de la décision. Par contre, la fusion multi-instance est basée sur la combinaison des empreintes palmaires droite et gauche, au niveau du rang.

Ces différentes méthodes de fusion ont prouvé leur efficacité en obtenant de meilleurs taux de reconnaissance, qui sont compétitifs par rapport à d'autres approches multimodales de la biométrie de la main.

Mots-clés: Biométrie, Forme de la main, Empreinte palmaire, Multimodalité, Fusion.

Biometry is a technology which is based on the personal identification using their physical features (fingerprint, hand geometry, palmprint) and/or behavioral features (voice, dynamic signature). Biometry aims to achieve two important goals in our current life. The first one is to ensure security by eliminating doubt regarding the identity of a person and the second one is to facilitate the identification of individuals. Indeed, this method of identification is increasingly preferred over traditional methods including passwords and badges. The research works of this thesis talk about the personal recognition using hand biometrics. The main objective is to design a multimodal biometric system based on the fusion of hand shape and palmprint modalities.

Our first part is to propose a new unimodal biometric system for hand shape verification. In fact, this system is based firstly, on the detection of the best set of keypoints located on the contour of the hand for further SIFT (Scale Invariant Feature Transform) description. On the other hand, a matching refinement based hand region and appearance is proposed in order to refine as much as possible false matched keypoints.

Our second part consists in the proposition of a new palmprint identification system. In fact, the sparse representation method is adopted in order to describe the palmprint biometric trait. It is based on the extraction on SIFT descriptors for each detected keypoint.

Our third part concerns the proposition of multi-type fusion methods for multimodality, including the multi-representation fusion, the multi-biometric fusion and the multi-instance fusion. Indeed, the multi-representation fusion method is based on the combination of SIFT descriptors and geometrical features of the hand, at score level. The multi-biometric fusion method is based on the fusion of hand shape and palmprint modalities, at feature and decision levels. On the other hand, the multi-instance fusion method is based on the combination of left and right palmprints, at rank level.

These different methods of fusion have proven their effectiveness by achieving encouraging recognition rates that are competitive to other popular multimodal hand biometric approaches.

Keywords : Biometry, Hand shape, Palmprint, Multimodality, Fusion.