



HAL
open science

Sift Based Recognition of Finger Knuckle Print

Baptiste Hemery, Romain Giot, Christophe Rosenberger

► **To cite this version:**

Baptiste Hemery, Romain Giot, Christophe Rosenberger. Sift Based Recognition of Finger Knuckle Print. The third Norsk Information security conference (NISK), 2010, Norway. pp.45-56. hal-00995114

HAL Id: hal-00995114

<https://hal.science/hal-00995114>

Submitted on 22 May 2014

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.

Redaktør: Patrick Bours, Norwegian Information Security Laboratory (NISLab),
Gjøvik University College

Norwegian Information Security Conference
Norsk Informasjonssikkerhetskonferanse

NISK 2010

Gjøvik University College, Gjøvik
23.–24. november 2010

Program Chair

Patrick Bours HiG

Program Committee

Kristian Gjøsteen	NTNU	Vladimir Oleshchuk	UiA
Tor Hellesest	UiB	Anders Paulshus	Conax
Erik Hjelmås	HiG	Ragnar Soleng	UiT
Audun Jøsang	UNIK	Nils Kalstad Svendsen	HiG
Martin Gilje Jaatun	SINTEF IKT	Svein Willassen	Svein Willassen AS
Stig F. Mjølnes	NTNU	Eli Winjum	FFI
Leif Nilsen	UNIK	Andre Årnes	HiG

Norwegian Information Security Conference
Norsk Informasjonssikkerhetskonferanse

NISK 2010

Gjøvik University College, Gjøvik
23-24 November 2010

Program Chair

Patrick Bours HiG

Program Committee

Kristian Gjøsteen	NTNU
Tor Hellesest	UiB
Erik Hjelmås	HiG
Audun Jøsang	UNIK
Martin Gilje Jaatun	SINTEF IKT
Stig F. Mjølnes	NTNU
Leif Nilsen	UNIK
Vladimir Oleshchuk	UiA
Anders Paulshus	Conax
Ragnar Soleng	UiT
Nils Kalstad Svendsen	HiG
Svein Willassen	Svein Willassen AS
Eli Winjum	FFI
Andre Årnes	HiG

© NISK-stiftelsen og Tapir Akademisk Forlag, 2010

ISBN 978-82-519-2705-5

Det må ikke kopieres fra denne boka ut over det som er tillatt etter bestemmelser i «Lov om opphavsrett til åndsverk», og avtaler om kopiering inngått med Kopinor.

Redaktør: Patrick Bours, Norwegian Information Security Laboratory (NISlab), Gjøvik University College

Tapir Akademisk Forlag har som målsetting å bidra til å utvikle gode læremidler og alle typer faglitteratur. Vi representerer et bredt fagspekter, og vi gir ut ca. 100 nye titler i året. Vi samarbeider med forfattere og fagmiljøer i hele landet, og våre viktigste produktområder er:

*Læremidler for høyere utdanning
Fagbøker for profesjonsmarkedet
Vitenskapelig publisering*

Forlagsredaktør for denne utgivelsen:
Lasse.Postmyr@tapirforlag.no

Tapir Akademisk Forlag
7005 TRONDHEIM
Tlf.: 73 59 32 10
Faks: 73 59 32 04
E-post: post@tapirforlag.no
www.tapirforlag.no

Preface

Welcome to NISK 2010, the third edition of the Norwegian Information Security Conference. After the initial NISK conference in Agder and its follow up in Trondheim, it will now take place in Gjøvik on the 23rd and 24th of November. As before the conference will take place in combination with NIK and NOKOBIT. NISK2010 is sponsored by NISnet, the resource network of Norwegian Information Security researchers funded by the Norwegian Research Council.

This year we had 27 high quality submissions from 8 different institutes. Of those one was withdrawn and one came in too late. The remaining 25 were reviewed by 2 members of the Program Committee each and from their feedback 14 papers were selected for presentation. This means that the acceptance rate of 56% is very close to the 58% from last year. All 14 papers will get a 30 minutes timeslot for presenting the ideas. Out of the 14 papers, 8 are authored or co-authored by PhD students and 1 is co-authored by master students.

We are glad to announce that Dr. Mike Bond from the Computer Laboratory at the University of Cambridge accepted the invitation as a keynote speaker. The title of his presentation is *Chip and Empiricism: Breaking EMV, with proof*. In May 2010 Mike Bond presented the controversial paper *Chip and PIN is broken*, which he co-authored with Steven J. Murdoch, Saar Drimer, and Ross Anderson, at USENIX Security. The paper described how an EMV card can be used to make purchases at Point-of-Sale without knowing the correct PIN. During the subsequent publicity, demonstrations of the technique deployed against the live banking system aired on various European television channels.

I would like to thank all the members of the Program Committee for their valuable input in the reviewing process. Furthermore I would like to thank the organizers of NIK, Erik Hjelmås and of NOKOBIT, Tom Røise for the pleasant cooperation and last but certainly not least I would like to thank Kari Lauritzen for all the help with the practical organization of the three conferences.

Table of Content

NISK 2010

Keynote

Chip and Empiricism: Breaking EMV, with proof	1
<i>Mike Bond</i>	

Session 1: Crypto

Coercion-Resistant Receipts in Electronic Elections	3
<i>Håvard Raddum</i>	
Algebraic Attack on the Second class of Modified Alternating \vec{k} -Generators	12
<i>Mehdi M. Hassanzadeh, Tor Hellesteth</i>	
Formal Verification of Reductions in Cryptography	21
<i>Kristian Gjøsteen, George Petrides, Asgeir Steine</i>	

Session 2: Biometrics

Accelerometer-Based Gait Analysis, A survey	33
<i>Mohammad Omar Derawi</i>	
Sift Based Recognition of Finger Knuckle Print	45
<i>Baptiste Hemery, Romain Giot, Christophe Rosenberger</i>	
Evaluation of Biometric Systems: An SVM-Based Quality Index	57
<i>Mohamad El-Abed, Romain Giot, Christophe Charrier, Christophe Rosenberger</i>	

Session 3: Hardware / Security

WinSCard Tools: a software for the development and security analysis of transactions with smartcards	69
<i>Sylvain Vernois, Vincent Alimi</i>	
Robustness of TRNG against Attacks that Employ Superimposing Signal on FPGA Supply Voltage	81
<i>Knut Wold, Slobodan Petrović</i>	
Security and trust for mobile phones based on virtualization	93
<i>Chrystel Gaber, Jean-Claude Paillès</i>	
Non-Invasive Reverse Engineering of the Relative Position of Bus Wires	104
<i>Geir Olav Dyrkolbotn</i>	

Session 4: Information Security Management

A Dynamic Approach to Security Management 110
Jose J. Gonzalez, Finn Olav Sveen
Enhancing Credibility of a Dynamic Model Involving Hidden Behavior 122
Jaziar Radianti, Jose J. Gonzalez

Session 5: Biometrics / Forensics

Secure and Privacy Preserving Management of Biometric Templates 134
Vincent Alimi, Rima Belguechi, Christophe Rosenberger
Storage and Exchange Formats for Digital Evidence 146
Anders O. Flaglien, Aleksander Mallasvik, Magnus Mustorp, André Årnes

Author Index 159

Sift Based Recognition of Finger Knuckle Print

Baptiste Hemery, Romain Giot and Christophe Rosenberger
GREYC laboratory
ENSICAEN - CNRS - University of Caen–Basse-Normandie
14000 Caen, France

{baptiste.hemery, romain.giot, christophe.rosenberger}@greyc.ensicaen.fr

Abstract

In this paper, we present a new unimodal method for finger knuckle print authentication. Previous works on this recent biometric modality mainly use image transform such as Radon, Gabor or Fourier. The proposed method is based on the computation of SIFT descriptors on the previously enhanced images of finger knuckle. Experiments on the recent PolyU FKP database show interesting results.

1 Introduction

Biometric-based authentication systems constitute one of the most promising candidates for either replacing or enhancing traditional systems based on secrets such as passwords and/or token like ID cards.

Hand-based biometric authentication has been largely studied thanks to the efficiency of fingerprint-based technology [1]. However, other modalities have been studied in the last decades: hand geometry [2], palmprint [2, 3] or palm and finger vein [4]. More recently, finger shape studies revealed that finger knuckle print are very discriminative [5]. Finger knuckle print (FKP) corresponds to the outer part of the finger around the phalangeal joint [6]. Recently, Zhang *et al.* enabled the community to work on this modality by releasing the PolyU FKP database [7].

Previous works on finger knuckle print [8, 9, 10, 11] mainly use transforms either locally or globally. Considered transforms are Radon, Gabor wavelet and Fourier. In [12], Kumar and Ravikanth also explore PCA, LDA and ICA analysis for finger knuckle print recognition.

The method presented in this work is based on the computation of SIFT descriptors [13]. This descriptor is generic and is used in object recognition, 3D stereovision or content based image retrieval. This method is inspired from our previous works on hand vein [4] and face recognition [14, 15].

This paper was presented at the NISK-2010 conference.

The paper is organized as follows. Section 2 presents the PolyU FKP database and previous works on FKP recognition. Section 3 presents the developed method and the obtained results are given in section 4. Finally, we conclude and give some perspectives of this work in section 5.

2 Finger Knuckle

Database

We use the PolyU FKP Database presented in [7, 11]. The acquisition device used to create the database can be seen in Figure 1. The database has been acquired on 4 fingers of 165 volunteers, leading to 660 different classes. There is no other database containing as many users. Each class contains 12 images acquired during 2 sessions. The first session, which corresponds to the first six images, constitutes the gallery set while the second session is the probe set.

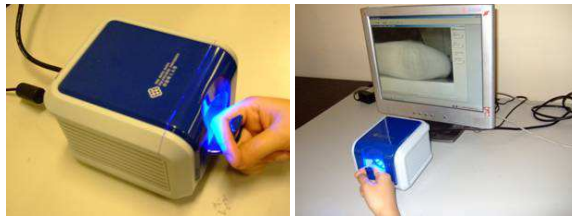


Figure 1: FKP acquisition device [7]

The database provides two sets of images. The first one corresponds to the whole acquired image. The second one corresponds to region of interest (ROI) images extracted from the first set of images. The ROI extraction is detailed in [10, 11, 16], and leads to gray level images of 110×220 pixels. Examples of acquired images are presented in Figure 2.

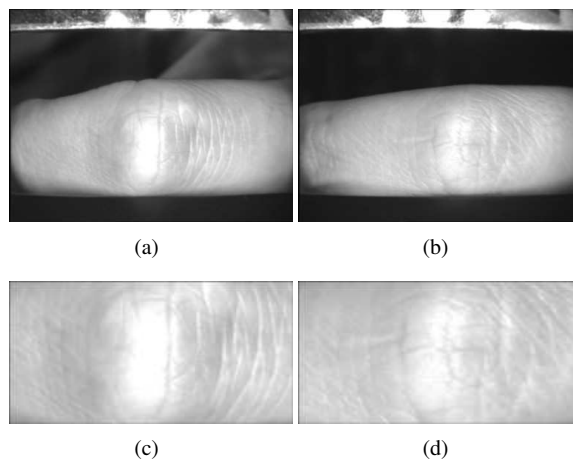


Figure 2: (a-b) FKP acquired images and (c-d) corresponding ROI

Related works

Woodward and Flynn [5] were among the first ones to study the feasibility of using the finger knuckle as a biometric modality. They acquired a database of hand with a Minolta 900/910 sensor, which enables the capture of a 3D model of the hand. The authentication method is based on the computation of the curvature based shape index, which represents the finger's surface. The normalized correlation coefficient is used to compute a match score. Such an approach leads to a 5% equal error rate (EER). This work is the first one indicating that finger knuckle print could be efficiently used as a biometric modality. However, the use of a 3D acquisition sensor limits its application.

Kumar and Ravikanth [12] studied the use of PCA, LDA and ICA analysis on FKP. The typical obtained EER was between 2% and 5%.

Later, Zhang *et al.* [10] proposed a competitive coding scheme (CompCode). This CompCode uses 2D Gabor filters to extract orientation information from FKP. The angular distance is used to measure the similarity between two CompCode maps. This approach leads to an EER between 1.5% and 2%.

Kumar and Zhou [8] proposed the same kind of approach. They suggested to use the robust line orientation code (RLOC) presented in [3]. This approach leads also to an EER between 1.5% and 2%.

Zhang *et al.* [11] also tried the Fourier transform of the whole image as the feature of the FKP. The band-limited phase-only correlation (BLPOC) technique was used to compute the match score. This approach leads one more time to an EER comprised between 1.5% and 2%.

All these methods are either local [5, 8, 10] or global [11, 12], but all fail to have an EER lower than 1.5%. Zhang *et al.* decided to fusion information from two local methods and created an improved competitive code and a magnitude code (ImCompCode&MagCode). This method slightly improves the performance with an EER of 1.48%. Actually, they are working on the fusion of local and global information (LGFF) [6], which clearly boosts performance with an EER below 0.5%.

In this paper, we propose a totally different unimodal approach for this biometric modality.

3 Developed Method

The developed method is local. However, we do not use Gabor wavelet as previous works in the domain. The method is based on an enhancement of FKP images, followed by a matching process of SIFT descriptors presented in our previous work concerning vein and face recognition using sift descriptors [4, 14, 15]. An overview of SiftFKP is shown in Figure 3.

Data extraction

Data extraction breaks down into two steps. The first one is an enhancement of a ROI image, while the second one is a SIFT key-points extraction and description.

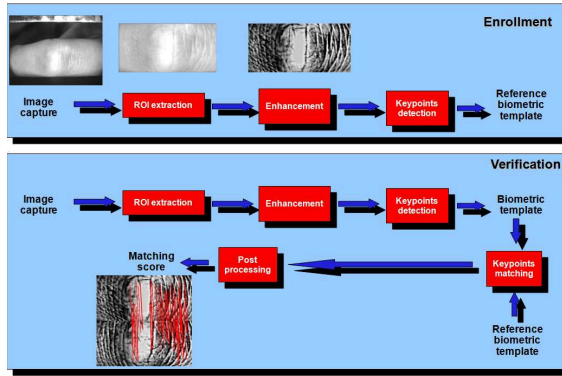


Figure 3: Overview of SiftFKP method

The ROI image enhancement used in this work is similar to the one proposed by Kumar and Zhou [8]. A background illumination is first computed by filtering the ROI image with a 10×10 filter divided by N . We tune $N=128$ to obtain a correct enhancement performance. The background is then extracted from the ROI image and a histogram equalization is processed. Images of the enhancement process are presented in Figure 4.

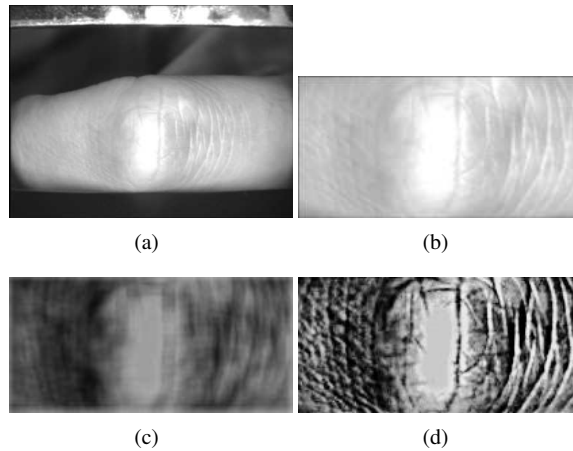


Figure 4: (a) FKP capture, (b) corresponding ROI, (c) background estimation and (d) enhanced image

We compute SIFT descriptors from the enhanced image. SIFT is a well known descriptor and has been largely used and studied since Lowe created it in 1999. The computation of a SIFT descriptor, as described in [13], consists of four stages: (i) scale-space peak selection, (ii) interest point localization, (iii) orientation assignment, and (iv) descriptor. The three first stages correspond to the localization of key-points. The descriptor is computed from a 4×4 location Cartesian grid. The gradient on each location bin is then quantized into 8 orientation bins, and is computed on the patch around the key-point. This leads to a 128-elements vector.

Matching process

The matching similarity principle that we used is described in our previous works in [4, 14, 15, 17]. Each enhanced ROI image im is described by a set of invariant features $X(im) = \{k_i = (s_i, x_i, y_i)\}$, $i = 1 : N(im)$ where s_i is the 128-elements SIFT invariant descriptor computed near key-points k_i , (x_i, y_i) its position in the enhanced ROI image, im and $N(im)$ the number of detected key-points for image im .

The verification between two images im_1 and im_2 comes down to computing a similarity between two sets of features $X(im_1)$ and $X(im_2)$. We thus use the following matching method which is a modified version of a decision criterion first proposed by Lowe [13]. Given two key-points $x \in X(im_1)$ and $y \in X(im_2)$, we say that x is associated to y if:

$$d(x, y) = \min_{\{z \in X(im_2)\}} d(x, z), \quad (1)$$

and

$$d(x, y) \leq C d(x, y'), \quad (2)$$

where C is an arbitrary threshold, $d(\cdot, \cdot)$ denotes the Euclidean distance between the SIFT descriptors and y' denotes any point of $X(im_2)$ whose distance to x is minimal but greater than $d(x, y)$:

$$d(x, y') = \min_{\{z \in X(im_2), d(x, z) > d(x, y)\}} d(x, z) \quad (3)$$

In other words, x is associated to y if y is the closest point from x in $X(im_2)$ according to the Euclidean distance between SIFT descriptors and if the second smallest value of this distance $d(x, y')$ is significantly greater than $d(x, y)$. The significance of the necessary gap between $d(x, y)$ and $d(x, y')$ is encoded by the constant C . Then, we consider that key-point x is matched to y if x is associated to y and y is associated to x .

Finally, we post-process associations to remove the wrong ones by checking that infinity norm distance between the position $Pos(\cdot)$ of key-points x and y in ROI images is lower than a threshold DP :

$$\|Pos(x) - Pos(y)\|_1 \leq DP \quad (4)$$

We can see on Figure 5 lines between associated key-points.

Once we have defined the associated key-points between images im_1 and im_2 , we define the similarity measure between these images $score(im_1, im_2)$ as the number of associations. The more associated points there are, the more ROI images are similar and supposed to be from the same finger.

Parameter settings

The SiftFKP method has two parameters: C which is used during the matching process and DP which is used during post-process. Parameter C varies between 0 and 1. A low value of C will lead to few associations while a higher value will lead to non-pertinent associations. Parameter DP is a distance between key-points and depends on the size of

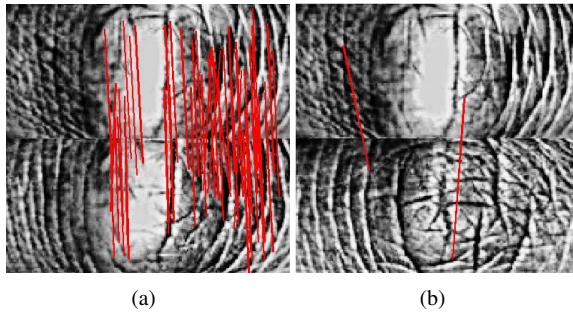


Figure 5: (a) Associations between two images (genuine, matching score=54) and (b) Associations between two images (impostor, matching score=2)

ROI images. In our case, it will vary between 0 and 220. A low value will be restrictive and remove too much associations while a too high value will not be able to remove wrong associations.

We tried different values for both parameters C and DP on a subset of the database containing 30 users (120 different fingers) as we can see in Figure 6, and we choose to set $C = 0.9$ and $DP = 40$, parameters leading to an EER of 0.76%.

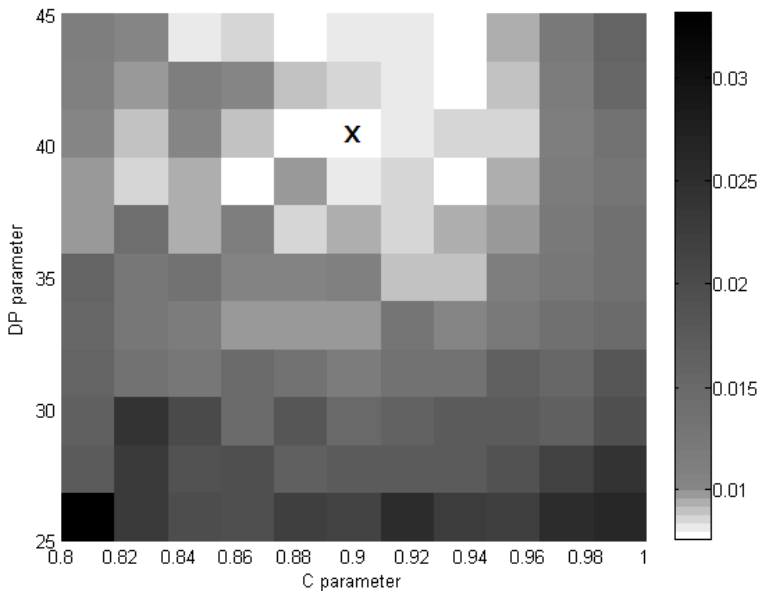


Figure 6: EERs (%) for different parameter values

4 Results

We reproduce the same experiments than in [16] on the PolyU FKP database. It consists in three experiments. The first one considers each finger as a different class. The second experiment looks after the performance with regards of the considered finger. Finally,

the third experiment indicates the performance of the system with the use of multiple fingers. We added a fourth experiment, considering that we can have up to 6 images for the enrollment of a user.

Experiment 1

In this experiment, all fingers are used and considered as coming from different individuals. The database contains 660 classes corresponding to 165 individuals and 4 fingers: Left Index (LI), Left Middle (LM), Right Index (RI) and Right Middle (RM). The enrollment set contains the 6 images from the first session while the test set contains the 6 images from the second session. Note, only one image is used for the enrollment of an individual. All images from the test set are match with all images in the enrollment set, leading to $660 * 6 * 6 = 23,760$ genuine matchings and $660 * 659 * 6 * 6 = 15,670,840$ impostor matchings. Obtained result is presented in Table 1, with corresponding confidence interval at 95% . The EERs for other methods are given by [16, 6].

Table 1: EERs (%) obtained in experiment 1

Method	EER(%)
CompCode [10]	1.72
RLOC [8]	1.93
BLPOC [11]	1.68
ImCompCode&MagCode [16]	1.48
LGFF [6]	0.40
SiftFKP	1.46± 0.08

We can see that SiftFKP performs quite well with an EER of 1.46%. It obtains approximately the same performance than the ImCompCode&MagCode. However, the proposed method does not use any fusion of information and thus performs better than CompCode, RLOC and BLPOC methods. The fusion of local and global information leads to a good performance of the LGFF method. The Score distribution and associated ROC curves given by the SiftFKP method are presented in Figure 7. We can see that the SiftFKP method permits to have a 0% FAR for an acceptable 3% FRR.

Experiment 2

The experiment 2 corresponds to the same computation on the same data. However, results are presented with regard of which enrollment finger is tested. Results are gathered in Table 2. Unfortunately, results from BLPOC and LGFF methods are not presented in [16, 6] for this experiment.

Table 2: EERs obtained in experiment 2

Method	LI	LM	RI	RM
CompCode [10]	2.06	1.96	1.82	1.87
RLOC [8]	2.20	2.27	2.07	2.32
ImCompCode&MagCode [16]	1.73	1.78	1.44	1.64
SiftFKP	1.38±0.25	1.24±0.13	1.97±0.29	1.64±0.01

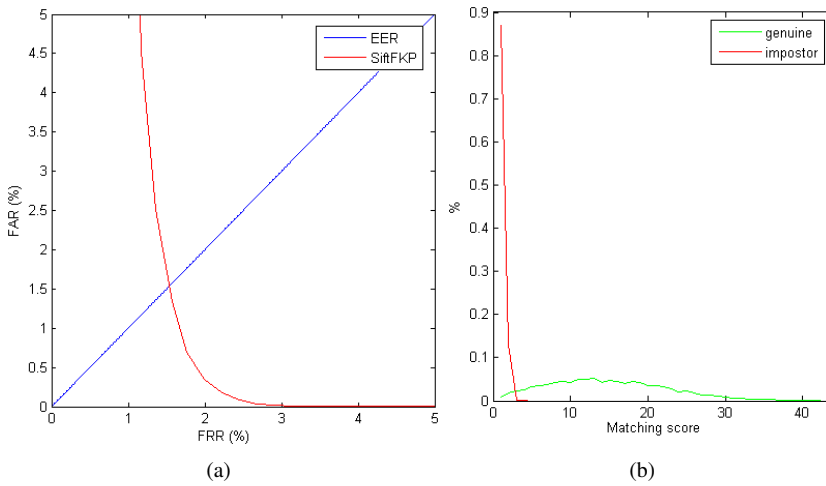


Figure 7: (a) ROC curve and (b) score distribution of Sift FKP method

We can see that SiftFKP method is still giving good results. Moreover, it seems that we can achieve a better recognition with left fingers than with right fingers, whereas other methods perform better on right fingers than left ones. ROC curves for each fingers are presented in Figure 8.

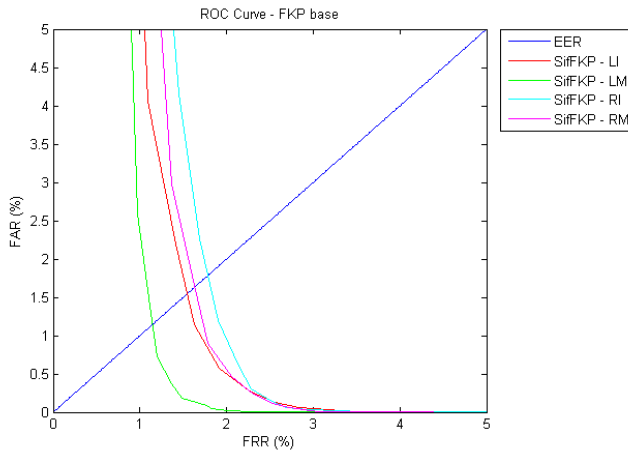


Figure 8: ROC curves for SiftFKP method - experiment 2

Experiment 3

Finally, the experiment 3 investigates the performance of the method when score based fusion is used. The aim of fusion is to improve the security of a biometric system. By using multiple fingers for one authentication, we should be able to more easily reject impostors. Moreover, it is also easier to accept genuine user, and thus, it also improves the usability of the biometric system. In [16], the SUM rule and MIN rule were investigated. It implies that the fused score is the sum, respectively minimum, of scores from two

fingers or more. The SUM rule gives better results than the MIN one. Thus, results obtained in this experiment are given in Table 3. We can conclude that using several fingers significantly improves the performance.

Table 3: EERs (%) obtained in experiment 3

Method	LI-LM	RI-RM	LI-RI	LM-RM	All
CompCode [10]	0.33	0.32	0.36	0.29	0
RLOC [8]	0.26	0.34	0.42	0.33	0
ImCompCode&MagCode [16]	0.20	0.26	0.26	0.27	0
SiftFKP	0.36 ± 0.01	0.25 ± 0.01	0.21 ± 0.01	0.20 ± 0.01	0 ± 0.004

The ROC curves for each different fusion are presented in Figure 9.

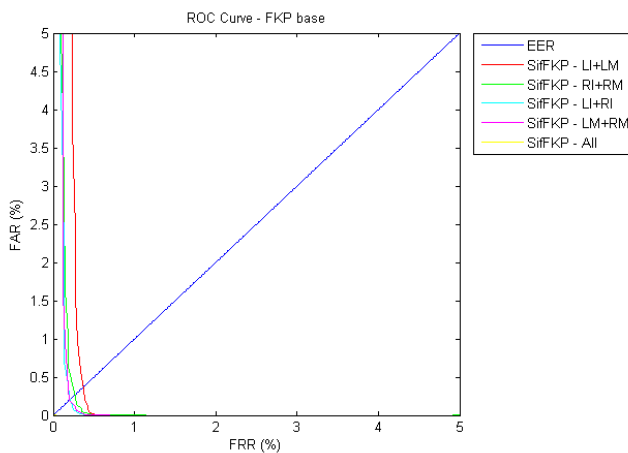


Figure 9: ROC curves for SiftFKP method - experiment 3

Experiment 4

In this experiment, we investigate the performance of the SiftFKP method when we fusion the score from several enrollment images. As in experiment 3, we consider the SUM method for the score fusion. We then proceed to the same experiment than before. The results obtained are presented in Table 4.

We present in Figure 10 the ROC curves for the experiment 1 with 1, 2, 3 and 6 enrollment images.

We can clearly see that the number of images used for the enrollment has an influence on performance. The more images there are, the better the performance is. Moreover, combining the use of several fingers leads to a very efficient modality. For instance, combining two fingers and only two enrollment images leads to a 0% EER. With one finger, having six enrollment images can also lead to a 0.25% EER.

Table 4: EERs (%) for different number of enrollment images

Number of enrollment images	1	2	3	6
experiment 1	1.46±0.08	0.78±0.02	0.54±0.002	0.40±0.05
experiment 2 - LI	1.38±0.25	0.42±0.04	0.39±0.004	0.25±0.007
experiment 2 - LM	1.24±0.13	0.73±0.03	0.53±0.02	0.37±0.02
experiment 2 - RI	1.97±0.29	1.01±0.03	0.48±0.02	0.40±0.00
experiment 2 - RM	1.64±0.01	1.01±0.006	0.66±0.09	0.67±0.03
experiment 3 - LI-LM	0.36±0.01	0.31±0.007	0.24±0.01	0.21±0.01
experiment 3 - RI-RM	0.25±0.01	0.10±0.001	0.11±0.01	0.09±0.002
experiment 3 - LI-RI	0.21±0.01	0.13±0.003	0.05±0.005	0±0.006
experiment 3 - LM-RM	0.20±0.01	0±0.003	0±0.00	0±0.00

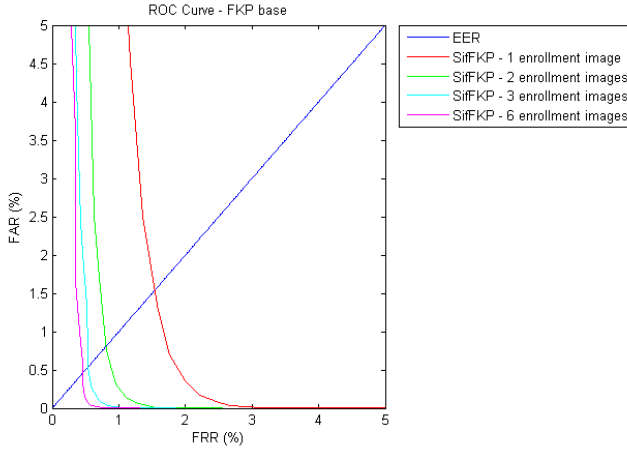


Figure 10: ROC curve for SiftFKP method - experiment 4

Analysis of errors

We looked for genuine ROI images that were difficult to recognize correctly. An example of such images is presented in Figure 11. Regarding several difficult genuine matches, we can conclude that the main problem for such difficult images is due to an important pose variation of the finger on the acquisition device. This leads to an important translation between the ROI images. Our method can manage translation within the limit of the DP parameter. In this case, the translation is too important to be correctly taken into account.

5 Conclusion And Future Works

We have seen that the proposed method for the finger knuckle print based on SIFT descriptors gives satisfactory results. It gives result equivalent or slightly better than the ImCompCode&MagCode method whereas it does not use any fusion.

However, we have seen that the LGFF method still gives better results. We can conclude that fusion of local and global information is pertinent as we have seen by analyzing the mistakes made by the proposed SiftFKP method.

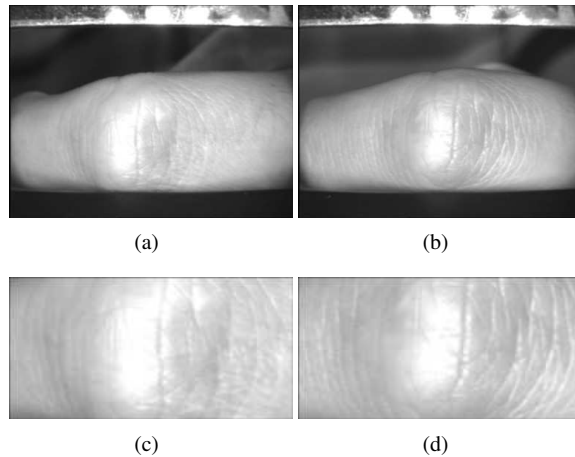


Figure 11: Difficult genuine matching: (a) enrollment image, (b) test image, (c) enrollment ROI image, (d) test ROI image

We have also seen that the fusion of several enrollment images increases the performance, and thus, the security of the system. With 6 images for the enrollment process, we can achieve a 0.25% equal error rate. With two finger, we are able to achieve a 0% equal error rate with only two images for the enrollment process.

In our future works, we aim to fuse information from local and global information. The local information would be the method presented in this work, whereas global information is going to be our future works.

References

- [1] AK Jain, A. Ross, and S. Prabhakar. An introduction to biometric recognition. *IEEE Transactions on circuits and systems for video technology*, 14(1):4–20, 2004.
- [2] A. Kumar, D. Wong, H. Shen, and A. Jain. Personal verification using palmprint and hand geometry biometric. *Lecture Notes In Computer Science*, pages 1060–1060, 2003.
- [3] Wei Jia, De-Shuang Huang, and David Zhang. Palmprint verification based on robust line orientation code. *Pattern Recognition*, 41(5):1504–1513, 2008.
- [4] Pierre-Olivier Ladoux, Christophe Rosenberger, and Bernadette Dorizzi. Hand vein verification system based on sift matching. In M. Tistarelli and M.S. Nixon (Eds), editors, *The 3rd IAPR/IEEE International Conference on Biometrics (ICB)*, pages 1297–1305. LNCS 5558, Springer-Verlag Berlin Heidelberg, 2009.
- [5] Damon Woodward and Patrick Flynn. Finger surface as a biometric identifier. *Journal of Computer Vision and Image Understanding*, 100:357–384, 2005.
- [6] Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu. Ensemble of local and global features for finger-knuckle-print recognition. *Pattern Recognition*, 2010.

- [7] Polyu fkp database. <http://www.comp.polyu.edu.hk/~biometrics/FKP.htm>.
- [8] Ajay Kumar and Yingbo Zhou. Human identification using knucklecodes. In *Proceedings of the IEEE International Conference on Biometrics; Theory, Applications and Systems (BTAS)*, 2009.
- [9] Ajay Kumar and Yingbo Zhou. Personal identification using finger knuckle orientation features. *Electronic Letters*, 45(20):1023–1025, 2009.
- [10] Lin Zhang, Lei Zhang, and David Zhang. Finger-knuckle-print: a new biometric identifier. In *Proceedings of the IEEE International Conference on Image Processing*, 2009.
- [11] Lin Zhang, Lei Zhang, and David Zhang. Finger-knuckle-print verification based on band-limited phase-only correlation. In *Proceedings of the International Conference on Computer Analysis of Images and Patterns*, pages 141–148, 2009.
- [12] A. Kumar and C. Ravikanth. Personal authentication using finger knuckle surface. *IEEE Transactions on Information Forensics and Security*, 4(1):98–110, 2009.
- [13] D.G. Lowe. Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2):91–110, 2004.
- [14] Christophe Rosenberger and Luc Brun. Similarity-based matching for face authentication. In *International Conference on Pattern Recognition (ICPR)*, 2008.
- [15] Baptiste Hemery, Jean-Jacques Schwartzman, and Christophe Rosenberger. Study on color spaces for single image enrolment face authentication. In *IAPR International Conference on Pattern Recognition (ICPR)*, Istanbul, Turkey, 8 2010. IAPR.
- [16] Lin Zhang, Lei Zhang, David Zhang, and Hailong Zhu. Online finger-knuckle-print verification for personal authentication. *Pattern recognition*, 43:pp. 2560–2571, July 2010.
- [17] Baptiste Hemery, H el ene Laurent, Bruno Emile, and Christophe Rosenberger. Comparative study of local descriptors for measuring object taxonomy. In *IEEE International Conference on Image and Graphics (ICIG)*, 2009.