Identifying individuals from average quality fingerprint reference templates, when the best do not provide the best results !

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Joannes FALADE*, Sandra CREMER* and Christophe ROSENBERGER*
* *Imprimerie Nationale Groupe France, Normandie Univ, UNICAEN, ENSICAEN, CNRS, GREYC, 14000 Caen, France*
Email: {Joannes.FALADE, Sandra.CREMER}@ingroupe.com, christophe.rosenberger@ensicaen.fr

***Abstract*—The fingerprint is one of the most used biometric modalities because of its persistence, uniqueness characteristics and ease of acquisition. Nowadays, there are large country-sized fingerprint databases for identification purposes, for border access controls and also for Visa issuance procedures around the world. The objective usually is to identify an input fingerprint among a large fingerprint database. In order to achieve this goal, different fingerprint pre-selection, classification or indexing techniques have been developed to speed up the research process to avoid comparison of the input fingerprint template against each fingerprint in the database. Although these methods are fairly accurate for identification process, we think that all of them assume the hypothesis to have a good quality of the fingerprint template for the first step of enrollment. In this paper, we show how the quality of reference templates can impact the performance of identification algorithms. We collect information and implement differents methods from the state of the art of fingerprint identification. Then, for these differents methods, we vary the quality of reference templates by using NFIQ2 metric quality. This allowed us to build a benchmark in order to evaluate the impact of these different enrollment scenarios on identification.**

***Keywords*-Biometrics, matching, indexing, fingerprint, minutiae, quality metrics, NFIQ2, Locality-sensitive Hashing.**

I. Introduction

Biometric systems use physical and behavioral characteristics (fingerprint, face, iris, hand shape, signature, gait) for people recognition. Fingerprint biometric systems are most used due to their properties as uniqueness, permanency and its ease of acquisition for government or private applications. For example, Aadhaar is the most large biometric database project (1 billion subjects) built for indian people recognition. For people administrative document as passport, ID card and residence permit, fingerprint is used as the biometric modality to identify the owner. Also, for migration issues and security against terrorist attack, many gorvernments use fingerprint databases to enhance the security of border control. For people recognition and in order to deliver authentic administrative papers, these large databases need to be searched on time. In general, biometric fingerprint systems have three functions: enrollment, authentication (verification) and identification.

The enrollment is the basic record function for all biometric systems. It consists in representing an individual uniquely by its fingerprint reference template that is associated with a corresponding identifier (name, pin, id) in the database. It is the first step of feature extraction and registration in database. The reference template must contain all the most reliable and discriminant information about each enrolled individual. That is why the quality of the reference template needs to be controled before the next two critical recognition tasks of authentication and indentification.

Authentication systems use an input fingerprint (sample or query) to verify or confirm if a person is what he/she claims to be. Thus, the verification task has to achieve comparison between an input fingerprint and some reference templates in the database; that's called 1-1 matching. Matching algorithms are evaluated through two performance metrics FAR and FRR. The FAR means False Acceptance Rate and FRR denotes False Reject Rate. The ultimate aim in the best case is to have both $FAR \to 0$ and $FRR \to 0$; that is called the compromise of verification systems because when one of these metrics tends to 0 the second pulls away from 0.

Identification systems use an input fingerprint and have as objective to check if the person has already been enrolled in the database before under another id. In this case, the system attempts to give result after searching against all entries of database. This identification task can be viewed as many successives verfications; That's why identification is called one-to-many or 1-N matching. In this case, identification requires a long computation time to carry out the verifications against all database entries. It has also been shown that doing all comparisons induces a high error rate in identification system performance [10]. Figure 1 describes all steps for different fingerprint systems functions.

So, classification, clustering and indexing strategies are important to achieve such an identification task in limited time. The first objective is to split and filter a large database in order to reduce the list of candidates to verify and the global identification time. This is measured by the Penetration Rate that we denote PR. $PR = \frac{\#candidates*100}{database\,Size}$. The second objective is to avoid

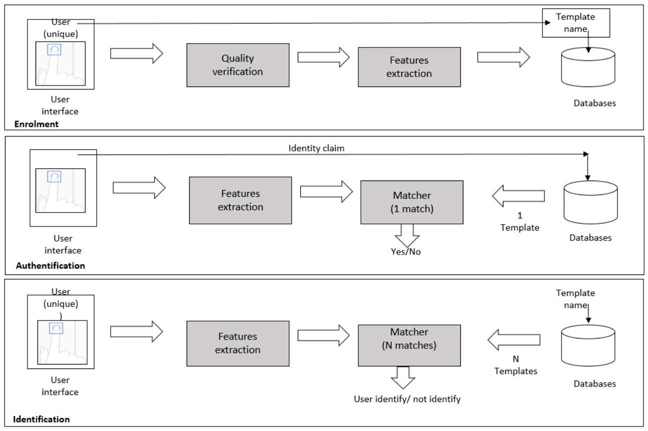

Figure 1. Three functions of enrollment, authentication and identification of fingerprint systems.

decreasing identification precision because of the candidate preselection step. This is measured by the Hit Rate we denote HR. $HR = \frac{\#Well\,Identified\,Candidates*100}{\#Total\,Identified\,Candidates\,Test}$. The ultimate aim in the best case is to have $PR \rightarrow 1$ and $HR \rightarrow 100$. That's called the compromise of identification systems because when $PR \rightarrow 1$, HR declines quickly. The major challenge for fingerprint identification comes from the difficulty of achieving both high speed and accuracy in recognition systems.

Many algorithms are proposed in the state of the art in the last decade to solve such an identification problem. These algorithms have different recognition and computation time performances; they are also treated in different conditions on different databases. We also think that identification algorithms can be more efficient with the constraint of choosing the ideal fingerprint reference for the step of enrollment. Notice that for the same finger, the image capture is different for each sample acquired several times. This is the real problem of enrollment because there is not unique features model for a fingerprint. In this paper, we provide a comparative study of different enrollment strategies with indexing algorithms for identification from the literature. We evaluate the impact of choosing the quality of the reference template during the enrollment process on performance for the identification step. We build a benchmark to compare all methods on the same databases and with the same conditions. To our knowledge, such a comparative study of fingerprint quality enrollment has never been proposed in the literature, this is our main contribution to an important topic in biometrics.

The rest of this paper is organized as follow. First, in section 2, we present various state of the art fingerprint indexing strategies for identification. Next, in section 3 we describe the proposed experimental protocol. We use the NFIQ 2.0 quality metric to change the quality of the reference template during the enrollment and finally provide comparisons between them. We conclude in section 4 and give an overview of perspectives.

II. Related works

For any biometric task, fingerprint features are extracted according two major strategies: one uses global features and the other one local features. For global features, fingerprint representation uses the core point, ridges shapes, ridges number and singular points such as delta and loop [14]. On the other hand, local features use fingerprint minutiae points and pores in order to build different solid geometrics or neighborhood features (Triplets, quadruplets, circle or cylinder arround minutiae) [10].

The problem we discuss in this work is about the impact of the quality of the reference template in order to get the best accuracy performance for identification task on large databases. In general, databases can be searched in three ways: classification, clustering and indexing. Classification is a supervised learning approach while clustering is known as unsupervised classification. Indexing techniques combine classification rules and clustering to realize a quick search in a database by assigning an index number to each database entry. In the special case of fingerprint database searching, classification and indexing are the most used methods to quickly search for a candidates list from a query fingerprint.

The basic method for the identification task is also known as the naive method in the state of the art. It consists in considering identification as multiple and successive verifications. For an input fingerprint I in the database, we try all possible verifications against all M fingerprints and return the best scores as candidates list. This method is experimental method and deterministic. The performance of identification is dependent of the matching algorithm that is used.

The Cascade method is a combination of successive naive methods. This method relies on using the advantages of many matchers to search the database. In general, the cascade is formed by the fastest matching algorithms at the front and the most accurate algorithm at the end. Indeed, generally the faster is a matching algorithm, the less precise it is. So, the cascade is built so as to quickly do a first preselection thank to the fastest algorithm and finish with the most precise algorithm for the last selection step.

The first classification method has been proposed by Henry [7] in 1900 based on global fingerprint feature extraction. He proposed to organize large fingerprint databases in five classes: right loop, left loop, whorl, arch and tented arch. In [9], Jain and al. also proposed a five-class based classification like Henry and tried to improve PR and HR. To achieve this performance, authors used the core point and built 48 areas of interest arround this point. They added a KNN algorithm to build the five classes so as to maximise the accuracy of the method. In [17], [1], [11], other authors worked on fingerprint database classification on five or at most nine classes. However, exclusive classification into five fingerprint classes is limited by the short number of classes and the fact that fingerprints are not uniformly distributed under the five classes defined by Henry. So, PR and HR can be improved and that is why fingerprint indexing methods are also most used in recent works.

Although, these new methods use an indexing strategy, they focus more on the representation of fingerprint as a discriminating factor. In [15], Parmar and Degadwala present a good, and useful review of fingerprint indexing methods. In [8] Iloanusi and al. present an original indexing fingerprint method based on minutiae quadruplets. Javad and Ali Khodadoust [13], [12] use an expanded Delaunay triangulation (triplets) and minutiae pairs to build an interesting fingerprint indexing method with good performances. Wei Zhou and al. [18] present a new triplets scheme for fingerprint indexing while in [2] authors propose a global method to reduce possible fingerprint index candidates lists. Notice that indexing methods are in general based on local features due to the fact that they are more discriminant. In [6], Arun Ross introduced an indexing method that we called the matcher method for fingerprint indexing. This method proposes to build a new input fingerprint index by using other specific fingerprints as references. Fingerprints which produce a high matching score variance against other fingers are chosen as references (discriminative property). These n reference fingerprints are very few (at most $5\% of M$). Then, Minutiae Cylinder Code (MCC) is a binary representation of a fingerprint proposed by Capelli et al. in [3]. Authors describe each minutiae of a fingerprint as a discretized cylinder which represents its neighborhood. In [4], an usefull algorithm is proposed for indexing MCC fingerprint during identification task.

III. Experimental protocol

We detail the protocol we used in this comparative study.

A. NFIQ2 Metric and enrollment

In this part, we present the fingerprint quality metric that we use for our experimental study about fingerprint quality during enrollment. The metric we use is NFIQ2 which all details is reported in [16]. NFIQ2 is the second version of NFIQ. NFIQ2 is a software developed by the NIST for fingerprint quality measurement. For each fingerprint, NFIQ2 returns a value between 0 and 100 related to the fingerprint quality. So, in order to compare two samples of fingerprint, notice that the best is the sample whith the high value of NFIQ2. NFIQ2 sometimes returns value 255 of out range when the quality cannot be computed for a fingerprint.

During our study, we simulate three scenarios during enrollment which are the Max, Mean and Min quality enrollment. As we explain in the section below, enrollment is the step of the first registration of an individual fingerprint in the database. We suppose that for this step, we get more than one sample of fingerprint of an individu and we have to choose one of these samples as reference. We compute the quality for all samples and save the best quality of NFIQ2 as enrollment reference in Max case. In Min case, we choose the worst quality of NFIQ2 as reference. About the Mean case, the image that we choose as reference is the NFIQ2 value of fingerprint which is the closest to the mean of all samples of fingerprint from an individual. In general, let's note that Max is the best case value of NFIQ2, the Mean is the Mean or normal case and Min is the worst case.

B. Fingerprint Databases

For experimental databases, we consider nine fingerprint databases from FVC competition. FVC 2000: DB1, DB2, DB3, DB4; 2002: DB1, DB4 and 2004: DB2, DB3, DB4. These fingerprint databases are the most used for testing, and particularly the 2004 databases which are considered as the most difficult ones. Each database contains 100 individuals and 8 samples per individual. We use one sample (using NFIQ2 metric) for enrollment and the other seven as query fingerprints.

C. Identification algorithms and parameters

Here, we present the algorithms we use for fingerprint identification in order to test our enrollment experiment protocol. We also present the set up of important parameters for each identification method as described in [5] in a previous comparative study of identification algorithms. To evaluate the impact of reference choice in identification performance, we consider four identification strategies from the state of the art that we have implemented. The identification methods we use are, the basic method, the cascade method, the matcher method and the MCC method. For each of these methods, we vary the three strategies of enrollment of individuals and we compute the CMC curve corresponding of each strategy to evaluate the differences.

For the basic, cascade and matcher identification methods, it is important to note that they are dependent on the matching algorithms. In table I, we show different matching algorithms we use to perform experimentations. We use four algorithms and notice that the higher the algorithm number is, the more accurate it is and the slower it is to perform a fingerprint comparison. $Algo4$ has better accuracy than $algo3$ but is slower.

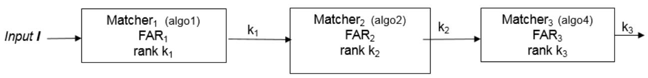

Figure 2. Cascade chain for fingerprint identification

In order to get a high bound limit for accuracy, we use $algo4$ for the basic method. Figure 2 shows that we use $algo1$, $algo2$, $algo4$ for cascade chain in our test. We use $algo3$ for matcher method and the rest of parameters to be fixed are written in table II. As MCC method does not depend on any matching algorithm for preselection, we set up MCC indexing method parameters in table III.

Matcher	$algo1$	$algo2$	$algo3$	$algo4$
FAR	0.095	0.078	0.04	10^{-2}
FRR	0.095	0.078	0.04	10^{-2}
t_i	10^{-1}	$1.1 * 10^{-1}$	$2 * 10^{-1}$	$6.7 * 10^{-1}$

Table I
Performance evaluation of used matching algorithms in terms of FAR, FRR and comparison time. Note that FAR value is equal to FRR in our case is expressed because we use the Equal Error Rate(EER) for our algorithm. t_i in millisecond. Note that $algo3$ is MCC 1-1 matching algorithm. The other algorithms are commercial ones.

Matcher method	Values
b	2
n	5
d	3

Table II
Matcher indexing method parameters we use for implementation. These values are chosen by reading [6] and set up the best parameters for our MCC matching algorithm which is the best suited for this indexing strategy.

MCC parameters	**Values**
n	1532
h	32
l	25
min	5

Table III
MCC indexing parameters we use for implementation. The min value is used in the MCC indexing algorithm to create reject and avoid considering minutiae with too much zero by hashing function.

D. Experimental results

The principle of the proposed method is to evaluate the impact of enrollment on the identification task. Although we did our experience on all FVC database, we decide to show and explain our result against FVC2000DB3 which generalize our observation and can be see as difficult database also. We also used the same minutiae extractor to build all fingerprint templates. We ensure this hypothesis because, in a previous study, we observed that the minutiae detection step is very important and discriminant for matching algorithms performance. For all databases, we compute CMC (Cumulative Matches Curve), a curve that combines PR and HR as the main performance tool for indexing methods. For implementation, we use C++ with no particular programming optimization. Our computers run with windows 7 on 2.60 GHz Intel core i7.

Figures 3, 4, 5, 6 show the performance of different identification methods against the same database FVC2000DB3 and the variations of the curves corresponds to each enrollment strategy. By observing the figures, we notice globally that the basic method and cascade have the best performance. These methods as we explain in [5] are theoretical, consume long time and unsusable for large databases. Mcc indexing is known as better than Matcher method which is considered as the worst approach.

Figures 3, 4 show that the better is the fingerprint reference, the better is the identification by using cascade method or basic because the green curve is the higher; the next is the orange and last is red which respectively represent the Max, Mean and Min reference enrollment. The reason of this is also that we compute at first all possibles (1-1) matching to make identification decision and our matching algorithms have a good recognition performance. These methods are totally deterministic. When we use a non deterministic method for identification like matcher and Mcc methods, the idea is to be more flexible, tolerate errors slightly on the enrollment step in order to be general during the identification task (general and probabilistic idea of the machine learning concept). Based on this concept, enrollment of the best reference as possible can be seen as overfitting. This situation can cause a trouble during identification step and especially if the identification method depends on global 1-1 matching result like the matcher method. The enrollment of the worst reference quality can cause the inverse of overfitting which is known as underfitting. So, to avoid this situation the mean enrollment strategy seems to be a good alternative as it can be seen on Figure 5 for the matcher method. As, the Mcc method is a very discriminative fingerprint representation, the CMC curve of identification shows a good robustness. But, our theory remains valid, because beyond a penetration rate of $PR > 30\%$, the CMC curve of Max, Min and Mean enrollment strategies are the same. Otherwise, using the strategy of Mean for reference enrollment is the best way in fact, the orange curve is the best when $PR < 30\%$ (see Figure 6).

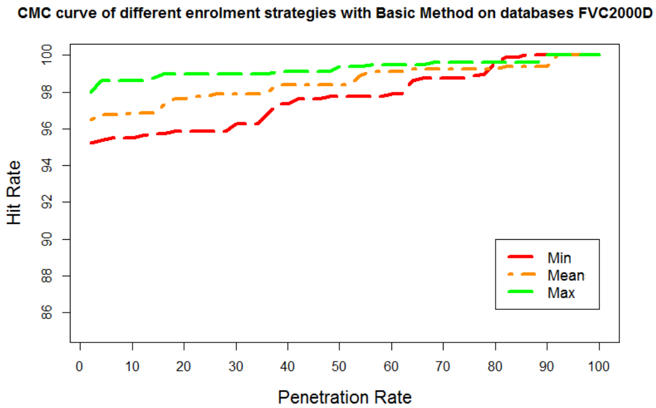

Figure 3. CMC identification performance on database FVC2000DB3 using basic method

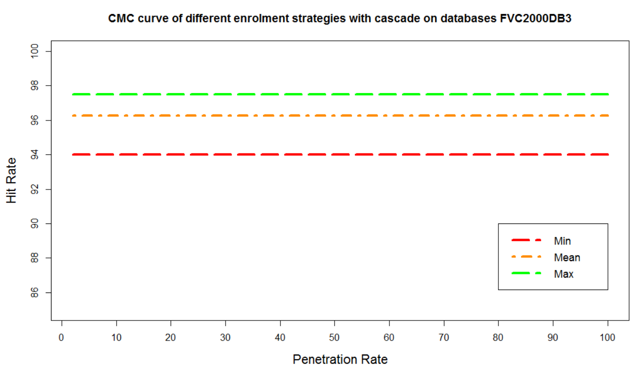

Figure 4. CMC identification performance on database FVC2000DB3 using Cascade method

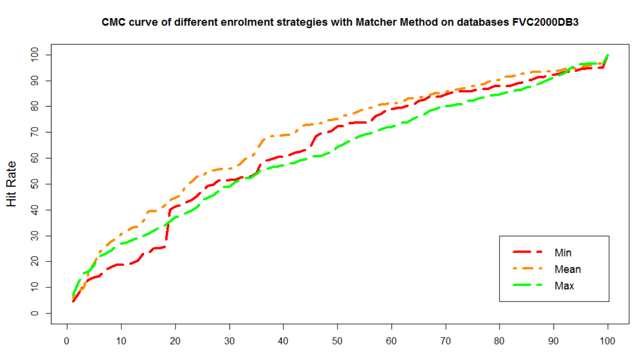

Figure 5. CMC identification performance on database FVC2000DB3 using Matcher method

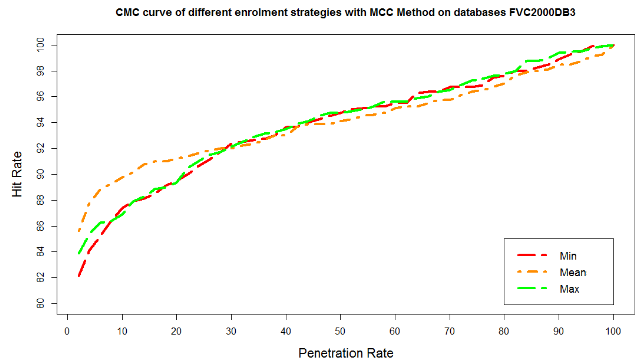

Figure 6. CMC identification performance on database FVC2000DB3 using MCC method

IV. Conclusion and Perspectives

This paper provides a study on the impact of the quality of reference templates on four fingerprint identification methods. We use a well known fingerprint quality assessment metric NFIQ2 to realize a real, simple and reproductible experiments on the effect of fingerprint quality enrollment during the identification step. In practice, for industrial purposes, the best sample reference is chosen but our study reveals that it is usefull sometimes to get the Mean quality for reference enrollment; that is to say not try to choose the best quality of fingerprint as reference and avoid also a very worst quality as reference too. Sometimes, the identification method which uses local representation of the fingerprint like Mcc seems to be more robust against enrollment variation. This study is done on FVC databases and our tests consist in identifying an input fingerprint in population of 100 people.

Perspectives of this study are to work on more large databases. We will realize tests on databases of ten million fingerprints generated by the Sfinge synthetic fingerprint. We are also continuing to implement other fingerprint identification methods from state of the art in order to provide a complete effect of enrollment strategies on identification methods. This will be helpful for all to get a real idea of state of the art and also to fix and correct the general idea of getting the best fingerprint quality as reference for identification.

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