Towards an Optimal Template Reduction for Securing Embedded Fingerprint Devices

Benoît Vibert, Christophe Charrier, Jean-Marie Le Bars and Christophe Rosenberger
Normandie Univ., UNICAEN, ENSICAEN, CNRS, GREYC, 14000 Caen, France

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Abstract: Template protection is an important issue in biometrics for security and privacy reasons. One solution for securing fingerprint data is to store it on a Secure Element (a microcircuit chipset such as a smartcard). An embedded On-Card-Comparison (OCC) module permits to compare two biometric templates and generates a similarity score. The biometric template is usually composed of minutiae extracted from the fingerprint image because a Secure element is limited in terms of memory and computation capabilities. For these reasons, a template reduction is necessary to quickly process fingerprint comparison. In this paper, we propose a new fingerprint template reduction scheme by approximating the optimal choice of minutiae with a genetic algorithm. We compared the proposed method with approaches from the literature using a fingerprint dataset and three matching algorithms. The experimental results show the benefit of the proposed method especially in order to estimate the optimal performance when reducing the fingerprint template given a number of minutiae to use.

1 INTRODUCTION

Nowadays, electronic transactions are part of our daily life (e-commerce, smartphones, physical access control ...). In order to guarantee the security of user authentication, biometrics is often used. Many real applications benefit from this technology such as for user access control or e-payment. According to (IHS, 2016), in 2020, the market of smartphones with a fingerprint sensor will reach 1.6 billions units. Nevertheless, a biometric data is very sensitive and cannot be revoked in general (like a password). In order to ensure its security and privacy, a biometric data is usually stored in a Secure Element (SE). The Secure Element could be a SmartCard, with an embedded On-Card-Comparison (OCC) algorithm for comparing two biometric templates.

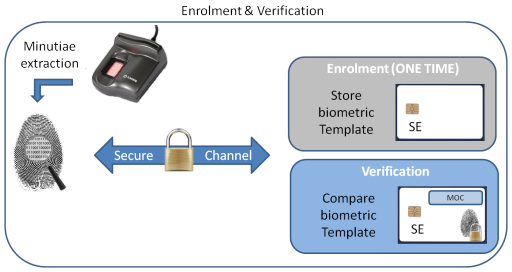

Figure 1: Enrollment and Verification step.

Two steps are necessary when using a biometric system: 1) the enrollment and 2) the verification as described in Figure 1. The OCC algorithm computes a comparison score between a captured biometric template and the reference one. The common fingerprint template is composed of a set of minutiae corresponding to specific points as described in Figure 2. The number of minutiae varies considering the used sensor but it is lower 80 in general.

Figure 2: Fingerprint minutiae.

As common practice, the biometric template stored in the SE follows the ISO Compact Card standard (ISO, b) to ensure the interoperability between biometric sensors and systems. This template is composed of a set of minutiae represented by 3 octets and 4 values $(x_i, y_i, T_i, \theta_i)$, $i = 1 : N_j$ where the coordinates (x_i, y_i) correspond to the location of the minu-

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tiae in the image, T_i corresponds to the minutiae type (bifurcation, ridge ending ...), θ_i to the minutiae orientation (related to the ridge) and N_j the number of minutiae for the sample j of the user.

A SE has hardware and software constraints such as the size of memory, the number of data we can send with an APDU command (ISO, c) (ISO 7816 standard for the communication with a SE). These limitations have an impact on the embedded algorithm and the size of the fingerprint template. The ISO/IEC 19794-2 standard recommends the maximal number of minutiae for enrollment and verification of the ISO-CC template is 60 (ISO, a). However, in an operational OCC application, a fingerprint template is usually limited to a specific number of minutiae which is lower or equal to 50 to satisfy the memory space, the APDU specifications and also the verification time (in general lower than 500 ms). In this case, it is necessary to reduce the template size when the extractor detected more minutiae.

Some automatic methods have been proposed in the literature such as the INCITS (Grother and Salamon, 2007) standard (called "Barycenter" on this study) which keeps only the minutiae closest to the CORE point. However, existing template standards are diverse, and mostly provide minutiae type instead of the quality of minutia point to assist the matching algorithm. Therefore, techniques for reducing the size of minutiae template without the quality information of a minutia point should be considered. Few works in the existing studies paid attention to this issue. The ISO organization (ISO, b) proposed a method based on peeling off minutiae (we call it "Truncation" in this study). Three other methods have been proposed by Vibert *et al.* (Vibert et al., 2015). The "evolutive Barycenter" is based on the method proposed by the NIST. A loop is used to re-compute the centroid when one minutiae is peeled off, until the number of minutiae expected is reached. The "Truncation Random Permutation" is based on the ISO organization method. With this method, the template of minutiae is shuffled, only the number of minutiae expected is kept on the final reduced template. "K-Means" is used as another approach where only minutiae closest than each cluster is kept on the final reduced template.

Yet, the main drawback of all of the above mentioned methods is that there is no guarantee to reach the optimal reduced template. For us, an optimal reduced template maximizes the similarity score with the original template for a selected OCC matching algorithm. In other words, all the obtained templates approximated more or less the optimal template without actually reaching it. The objective of this paper is to approximate as close as possible the optimal reduction of a minutiae template. This approximation provides a landmark to determine whether it is worth to look for better practical reduction methods. To our knowledge, this is an original contribution of this paper.

The proposed approach is presented in section 2. Section 3 provides the experimental protocol. Evaluation results are discussed in Section 4. Section 5 concludes this study and gives the associated perspective.

2 PROPOSED METHOD

The general framework of this study is a two-step work: 1) minutiae acquisition and 2) performance evaluation. The acquisition involves two tasks which are illustrated in Figure 3. We first use an extractor to generate full-size minutiae template and then perform selection operations considering the desired minutiae number to obtain the reduced template. The quality of the reduction is linked to security and usability since it has an impact on performance, especially on FAR (False Acceptance Rate) and FRR (False Rejection Rate).

In this paper, we propose a Minutiae Reduction with Genetic Algorithms scheme (namely MRGA) to estimate the optimal reduction of any minutiae template. Given a template containing N minutiae, we want to determine the optimal reduced template containing N_{max} minutiae (under the constraint $N_{max} < N$), *i.e.*, providing the best performance. To be sure to determine this optimal template, we should test $\binom{N}{N_{max}}$ possibilities (number of combinations of N_{max} elements among N) that is not possible. To achieve this goal, the proposed method is based on the use of genetic algorithm (GA).

A genetic algorithm is a method for stochastic search introduced in the 70s by John Holland (Holland, 1975) and by Ingo Rechenberg (Rechenberg,). Genetic algorithms allow to determine the optimal value of a criterion by simulating the evolution of a population until the survival of the best individuals (Wall, 1996). The survivors are obtained by selection, transformation or crossing of the previous generation. We estimate that the optimal search function is a non-linear multidimensional function, usually characterize by several minima. Therefore, the search strategy should find the global minimum, and avoid remaining trapped in local minima. The objective is to obtain a reduced minutiae template having the best performance compared to the original template applying an OCC algorithm. A genetic algorithm is defined by five essential elements:

1. **Genotype:** This is a set of characteristics rep-

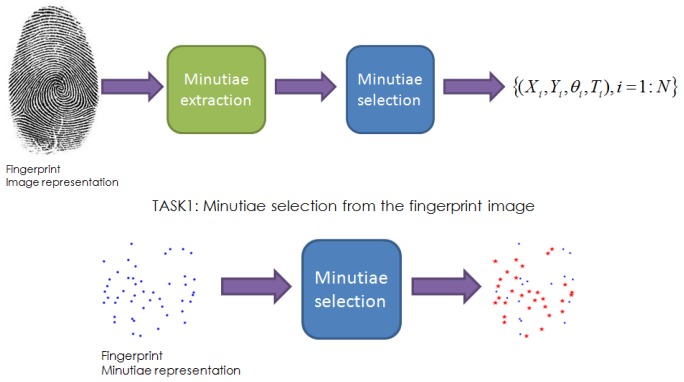


Figure 3: Two tasks involved in template reduction.

resenting each individual in the population. In our case, the initial population consists of 500 individuals composed of N elements, N being the desired number of minutiae within the reduced biometric template. As we want to get a template with minutiae existing in the initial template, the population will be constituted by random draws of N minutiae in the initial template containing M minutiae.

2. **Initial Population:** This is a set of individuals randomly drawn from the original template. Each individual consists of N elements. Each element corresponds to a unique minutiae present in the original template.

3. **Evaluation Function:** It measures the quality of an individual. If we consider individual I_1 to evaluate, we compare it with the original template using an OCC and we get an $S(I_1)$ score. The evaluation function is based on the OCC computation, since it is fast to compare two biometric templates and it has good performances. This algorithm returns us a similarity score between the two templates. The higher is the similarity score is, better is the tested individual *i.e.*, the reduced template.

4. **Operations on Genotypes**: the genes of the individuals are modified by the use of three functionalities:

   - *Selection:* Individuals that do not match the environment (insufficient score) are not selected. To do this, we apply the elite mode (the 5 individuals with the highest score are kept in the next generation).
   - *Crossing:* the genes resulting from the crossing of two individuals is a combination of the genes of its parents. To obtain the individual resulting from individuals I_1 and I_2, we look at the elements present in the two individuals without the duplicated ones and randomly select the first N elements. We thus obtain an individual (son) mixing the genes of the two individuals (parents). As a result, the resulting minutia template contains minutia from both parents.
   - *Mutation:* Random genes are modified in order to adapt to the environment. We randomly draw an individual, then we cross this individual with an elite individual. The resulting individual I_r = mutation (I_1) = cross(I_1, I_a) with the random individual. It makes it possible to obtain an individual having genes from an elite individual crossed with genes of a random one.

5. **Termination:** This is the end-of-evolution criterion depending on the score of individuals or the number of generations. If an individual keeps the same score for 10 generations or 500 generations have been made, the algorithm ends.

We summarize here the work-flow of the execution of a genetic algorithm:

1. Definition of initial population of 500 individuals,
2. Evaluation of Individuals,
3. Generation of the population at current generation:
   - Selection of 5 elite individuals;
   - 30 % of the population (here 150 individuals) is obtained by mutating elite individuals with random ones;

- 30 % of the population (here 150 individuals) is obtained by crossing elite individuals;
- Selection of random individuals to complete the population.

4. Return to step 2 if the stopping criterion is not satisfied.

The next section presents the results obtained with MRGA method in comparison with some state-of-the-art methods.

3 EXPERIMENTAL PROTOCOL

To evaluate the performance of the MRGA method, we need to make some choices about biometric database, minutiae extractor, comparison algorithms and performance metrics. We detail these aspects in the following sub-sections.

3.1 Database

In this study, the FVC2004DB1 fingerprint database from the Fingerprint Verification Competition (FVC) (www,) is used. This database is composed of 800 images from 100 individuals with 8 samples from each user. The image resolution is 640×480 pixels acquired with an optical sensor "V300" by CrossMatch. Figure 4 shows some examples of fingerprints in this database.

Figure 4: Example of fingerprint images in the FVC2004DB1 database.

3.2 Minutiae Extractor

The minutiae templates used in the experiment have been extracted using the NBIS tool, and more specifically MINDTCT (Watson et al., 2007) from the NIST. We used this extractor because it is widely used in academic research.

3.3 Matching Algorithms

In this study, we used three matching algorithms:

1. **Bozorth3** (Watson et al., 2007). This comparison algorithm uses only the locations and orientation of the minutiae to match the fingerprints. We get a similarity score as output of the algorithm.
2. **Minutia Cylinder-Code (MCC) Algorithm** (Cappelli et al., 2010). The representation of MCC associates a local structure with each minutia. This structure contains the spatial and directional relationships between minutia and its neighborhood (fixed radius). Each structure is invariant in translation, rotation, distortions and small errors of extraction of characteristics. A double measure of similarity is computed and consolidated to provide an overall score for comparison.
3. **Commercial OCC.** We do not have information on how this algorithm works since it is a commercial one. As output of the algorithm, we do not have a score but simply a decision result of type "Accepted" or "Declined".

3.4 Evaluation Metrics

In order to assess the performance of a biometric system, we can use the Receiver Operating characteristic Curve (ROC). This curve plots the False Match Rate (FMR) (*i.e.*, accepted impostor attempts) on the x-axis against the corresponding False Non-Match Rate (FNMR) (*i.e.*, rejected genuine attempts) on the y-axis. This curve is parametrically plotted as a function of the decision threshold. An example of a ROC

curve is presented in Figure 5. The area under the curve (hatched zone) should be as low as possible to minimize recognition errors. The associated measure is called AUC (Area Under the Curve) and is often considered as a global performance criterion. We use this value in this paper to quantify the efficiency of all trial minutiae selection methods.

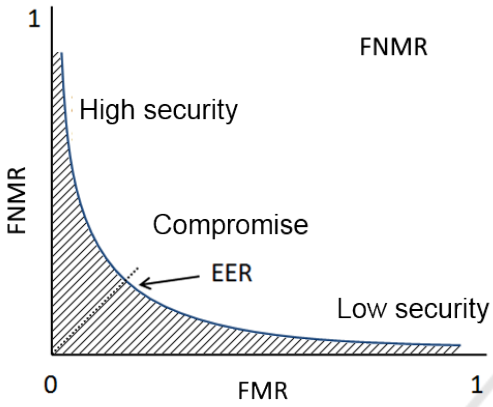


Figure 5: Definition of the ROC curve: evolution of the False Match Rate face to the False Non Match Rate.

The first sample from each individual is chosen as reference template while other seven samples are used for tests. With a matcher, we generate a group of intra-class matching scores (GMS) and a group of inter-class matching scores (IMS) for each dataset. The evaluation result is indicated by the global AUC value computed from the two groups of matching scores. This computation is done for every group of reduced templates. A curve of AUC values obtained for different sizes of the reduced template is plotted to compare one reduction algorithm with others. For each of the AUC value, we calculated the associated confidence interval (CI), which allows us to have an additional precision for our results. Since we use a small number of data for the evaluation, the confidence interval gives us additional information on the accuracy of the results. Another important criterion in our study is the computation time needed for the reduction of a biometric template.

4 EXPERIMENTAL RESULTS

First of all, we have to build the baseline performance by using the original template.

4.1 Performance Evaluation of MRGA

Table 1 shows the AUC value for the original template that will serve as baseline performance to compare the performance of other methods with. We notice a much better performance of the commercial OCC. We then compute the AUC value and its associated confidence interval for each reduction method with N_{max} varying from 30 to 50 in steps of 4. We observe that the NIST comparison algorithm as well as the MCC scheme have much worse performance than the commercial OCC. This is not so many surprising since commercial algorithms are supposed to have high performance level.

Table 1: AUC values for FVC2004DB1 database with Bozorth, MCC and the commercial OCC.

Bozorth	MCC	commercial OCC
11.1% ± .18	18.4% ± .17	3.77% ± .09

Figure 6 presents the evolution of the fitness score until the stopping criterion is reached. After 70 generations, the reduction of the template scheme provides a solution close to the optimal reduced template. The blue line represents the average fitness score obtained during the generations. The black line is the best fitness score obtained for each generation. We can observe that the optimal reduced template is obtained after few generations.

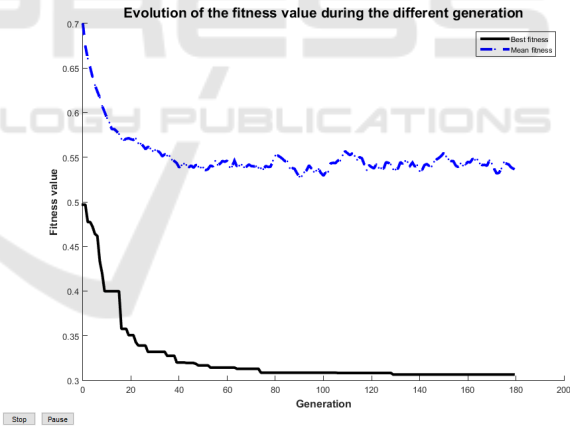
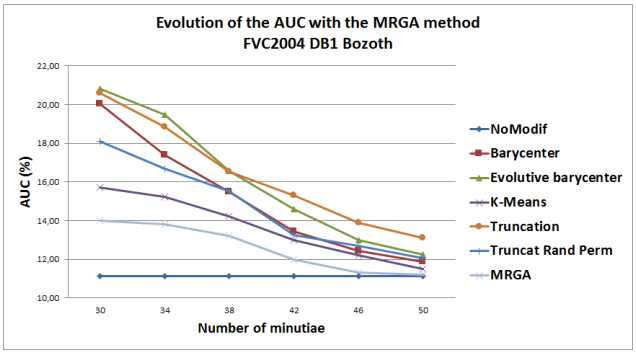


Figure 6: Evolution of the Fitness score.

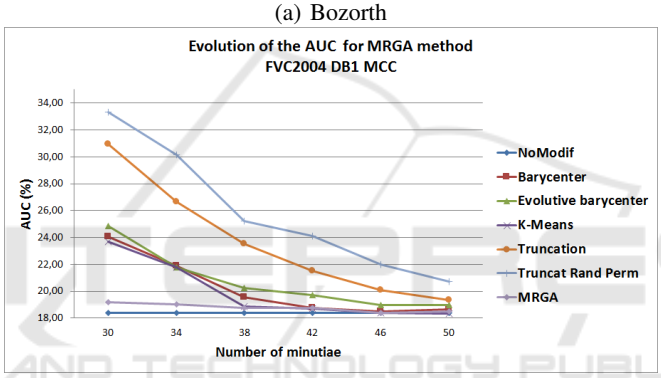
Obtained performances using the trial matching algorithms are summarized in Table 2. We display the obtained results using the MCC algorithm too, even if it has been used in the evaluation function of the genetic algorithm. This allows us to observe if we have a performance close to the initial template. We observe that the proposed MRGA method provides performance almost similar to the initial template, as it could expected. We can conclude that the reduced templates obtained with the MRGA method obtain a performance very close to the original templates for all the matching algorithms.

Table 2: Difference between AUC values for the initial template and MRGA method for different values N_{max} of minutiae on FVC2004DB1 for all OCC algorithm.

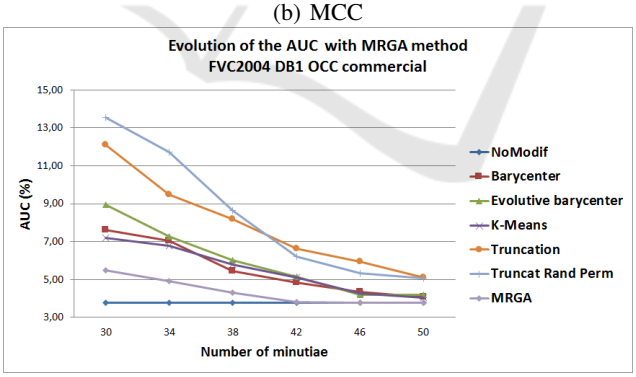
OCC	Initial Template	30	34	38	42	46	50
Bozorth3	11.1% ±.18	+2.9%±.46	+2.71%±.32	+2.1%±.28	+0.9%±.28	+0.2%±.26	+0.1%±.24
MCC	18.4% ±.17	+0.8%±.17	+0.6%±.16	+0.4%±.15	+0.3%±.12	0%±.12	+0.1%±.09
Commercial	3.77% ±.09	+1.73%±.25	+1.13%±.24	+0.55%±.21	+0.03%±.20	0%±.18	0%±.14



(a) Bozorth



(b) MCC



(c) commercial OCC

Figure 7: Comparison of the MRGA method with the best reduction methods applied on FVC2004DB1 database for the three fingerprint comparison algorithms.

Table 3 presents the average time needed to reduce a biometric template when the MRGA method is used. This reduction has been made on Matlab running on a computer (PC) with a Intel Core I7, quad-core with a frequency at 2.8Ghz and 16GO of RAM. These times have to be considered for a relative comparison. These computation times could be easily reduced if the computation is made on server in C++, that could be least 10× more efficient.

Table 3: Average time to perform the reduction for different values N_{max} of minutiae when MRGA method is used.

N_{max}	30	34	38	42	46	50
Time	38 min	35 min	28 min	20 min	18 min	13 min

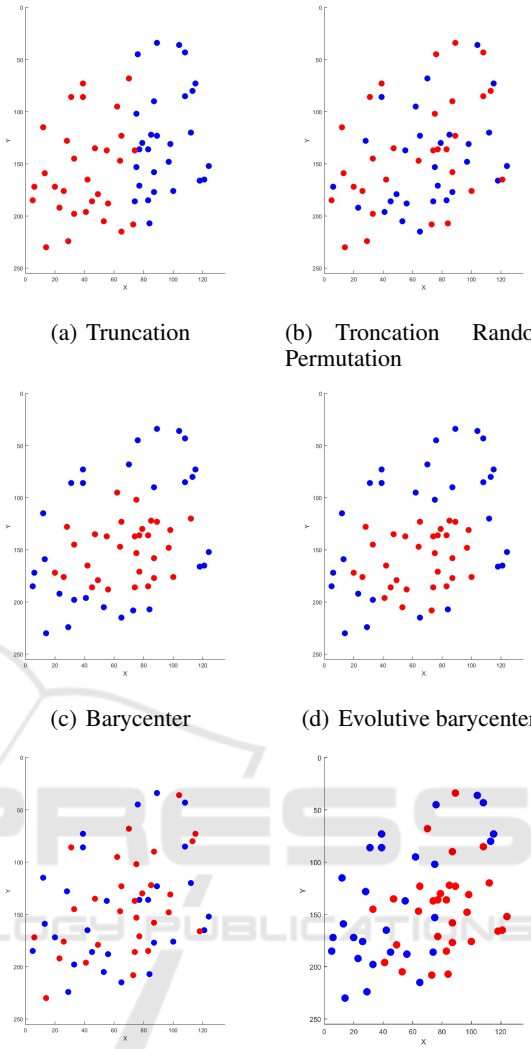
Considering computation times, this method cannot be used in an operational framework but only for validation purposes. Nevertheless, we could imagine to use it if the computations are done on a server. During enrollment, the reduced biometric could be computed online and sent in a secure way to the secure element.

4.2 Comparison with State-of-the-art Methods

We want to evaluate in which way some state-of-the-art methods, Truncation, Barycenter, Evolutive Barycenter, Truncation Random Permutation and K-Means, are close to the "optimal" reduced template. Figure 7(a) for the Bozorth3 algorithm, figure 7(b) for the MCC algorithm and figure 7(c) for the commercial OCC show the comparison results.

We could note that the trial methods are more or less close to the MRGA method especially for large number of minutiae. This allows us to better understand whether a change in methods is possible to achieve the best possible reduction. We can observe from Figure 7(b) with MCC matching algorithm, that K-means method provides the best reduced template when the number of minutiae ranges from 38 to 50. For Bozorth3 matching algorithm (Figure7(a)), K-means is the best method but, we could improve it to reduce the gap with the MRGA method. Considering the commercial OCC, the three state-of-the-art methods are very close to the performance of the initial template showing the benefit of MRGA.

Figure 8 shows the initial template, in blue on each figure, and the associated selected minutiae (red dot) when we applies: Truncation, Barycenter, Troncation Random Permutation, Evolutive barycenter, K-Means and the MRGA method. We observe that, the best method for reducing the minutiae template, K-Means and MRGA, have a good minutiae spatial distribution on the fingerprint image. If we analyze with more details the MRGA reduction template we could observe, it is a combination of Barycenter approach and K-Means.



(a) Truncation (b) Troncation Random Permutation

(c) Barycenter (d) Evolutive barycenter

(e) K-Means (f) MRGA

Figure 8: Illustration of a reduced fingerprint template for each method of the state-of-the-art and the MRGA method on the initial template (in blue on each figure).

5 CONCLUSION

When we want to have secure device to store your biometric data, you use a SE. When we want to increase the security of the matching algorithm, we have to store very efficient biometric data on it. SE are limited in term of memory size, this is why we need to have methods which permit to reduce the size of the biometric template.

Few methods have been proposed on the state-of-the-art and we want to estimate in what way we are close to the best reduction. The purpose of this paper is to find a solution for estimating the best reduced minutiae template for different templates size. Thus, we could increase the security of embedded fingerprint systems. On the state-of-the-art, no method which permit to estimate this "optimal" template that is why we proposed the MRGA approach. We have used one database FVC2004DB1 and three matching algorithms to test the performance of this method. We have shown that the MRGA is for all matching algorithms the best method and is close to the initial template in term of performance. We could consider we obtain the upper value performance and template in

comparison with the initial template. We observe than some methods are closer to the MRGA method when we have a high number of minutiae on the reduced template. In opposition, when we have a small number of minutiae, we have many ways to improve the reduction and obtain better performance and security. With this study, we proposed an approach to evaluate the upper performance for peeling off the minutiae template. This method could be used on server when enrollment part is done, to increase the efficiency of the matching algorithm.

As perspectives, we want to analyze and proposed new methods to reduce the initial template to be closer to the ”optimal” reduced template provided by the MRGA method.

REFERENCES

Fvc2004db1. http://bias.csr.unibo.it/fvc2004/databases.asp.

ISO/IEC 19794-2. information technology - biometric data interchange format format - part 2 : Finger minutiae data, 2011.

ISO/IEC 19795-2. information technology - biometric performance testing and reporting - part 2 : Testing methodologies for technology and scenario evaluation, 2007.

Cappelli, R., Ferrara, M., and Maltoni, D. (2010). Minutia cylinder-code: A new representation and matching technique for fingerprint recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(12):2128–2141.

Grother, P. and Salamon, W. (2007). Interoperability of the iso/iec 19794-2 compact card and 10 iso/iec 7816-11 match-on-card specifications 11.

Holland, J. H. (1975). *Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence.* U Michigan Press.

IHS (2016). Fingerprint sensor market growth continues upward trajectory, ihs says. https://technology.ihs.com/571358/fingerprint-sensor-market-growth-continues-upward-trajectory-ihs-says.

ISO. *ISO/IEC 7816-1 to 15: Identification cards - Integrated circuit(s) cards with contacts(Parts 1 to 15)*. ISO/IEC, http://www.iso.org.

Rechenberg, I. Evolutionsstrategie94. frommann-holzboog-verlag, stuttgart (germany), 1994. *German; includes also*, 1581.

Vibert, B., Charrier, C., Le Bars, J.-M., and Rosenberger, C. (2015). Comparative study of minutiae selection algorithms for iso fingerprint templates. In *SPIE/IS&T Electronic Imaging*, pages 94090C–94090C. International Society for Optics and Photonics.

Wall, M. B. (1996). *A genetic algorithm for resource-constrained scheduling*. PhD thesis, Massachusetts Institute of Technology.

Watson, C. I., Garris, M. D., Tabassi, E., Wilson, C. L., Mccabe, R. M., Janet, S., and Ko, K. (2007). User's guide to nist biometric image software (nbis). Technical report, NIST.