Fingerprint Class Recognition for Securing EMV Transaction

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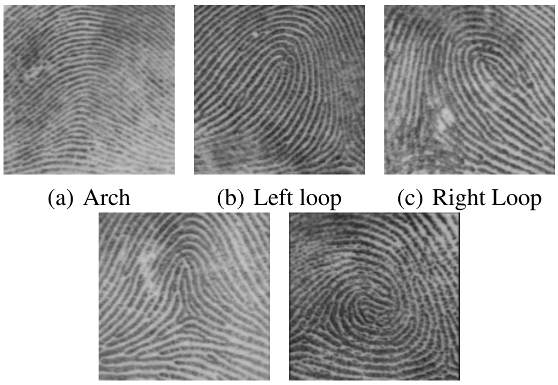
Abstract: Fingerprint analysis is a very important issue in biometry. The minutiae representation of a fingerprint is the most used modality to identify people or authorize access when using a biometric system. In this paper, we propose some features based on triangle parameters from the Delaunay triangulation of minutiae. We show the benefit of these features to recognize the type of a fingerprint without any access to the associated fingerprint image.

1 INTRODUCTION

Fingerprint is usually associated to criminal investigation, since it is the oldest use case commonly known by people and is well established in the human mind. This can be a reason why such biometric modality is quite well accepted and used by people to unlock access on mobile devices or web services. In addition, this kind of authentication yields to reach a high level of trust in the security and privacy protection of dematerialized transactions. That way, fingerprint became in few years a very popular biometric modality for such use cases. In 2013, the first smartphone embedding a fingerprint sensor has been deployed for public use. In order to guarantee security and privacy issues, the fingerprint processing is realized on a Secure Element (SE) such as a SIM card or smartcard.

However SE is limited in computation process and memory size. Due to this latter, it is not possible to store the entire fingerprint image inside. The image is then processed in order to obtain a relevant and compact representation. This representation is based on particular points of the fingerprint, known as minutiae. Yet, all extracted minutiae, referred to as minutiae template, can not be entirely stored inside a SE. Actually, any minutiae template stored within a SE should be in compliance with the ISO Compact Card II (ISO, 2011) standard which provides the maximum number of used minutiae that can be stored inside a SE. Basically, a minutiae is described by its location, type and orientation. All those informations are stored inside the SE. When an authentication process is required, a template comparison is performed between the embedded template and the request one to determine how they are similar. This comparison step is computed inside the SE using an embedded On-Card-Comparison (OCC) module (Cf. Figure 2). Another important feature about fingerprint concerns its type. Even if a fingerprint is considered as unique, it necessarily corresponds to one of the five classes (know as Henry classes) as defined by Henry: Arch, Left Loop, Right Loop, Tented arch and Whorl, as illustrated in Figure 1.

This compliant standard representation can be usefull for Europay Mastercard Visa (EMV) transactions with biometric authentication. Indeed, since 2015, the EMVco (EMVCo, 2008) allows to use biometric data in the Cardholder Verification part (Figure 3). This is the context of this study that justifies the use of the ISO Compact Card II representation instead of any other existing representation. In return, new kinds of attack can be performed on SE.



(a) Arch (b) Left loop (c) Right Loop (d) Tented arch (e) Whorl

Figure 1: The five classes of fingerprint defined by Henry.

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Among all possible attacks, one concerns the detection of the class of the minutiae template, as defined by Henry. The main assumption can be formulated as follows: how the knowledge of the class of the minutiae template increases the attack success ? How the knowledge of the template allows to determine the class of the fingerprint ? In (Vibert et al., 2016), the authors argue that the knowledge of the class of the fingerprint significantly helps the attacker to succeed from 2% to 50%. Based on this work, we investigate how it is possible to block this kind of attack. One way is to considered the addition of a mechanism on the Payment terminal and the SE which permit to detect the fingerprint class. The fingerprint class is include in the Cardholder Verification Result (CVR) and send to the terminal to process the Terminal Risk Management and detect if the template type is different between the one sent by the terminal and the template received by the smartcard. In this way, we investigate if the detection of a fingerprint class change between the card and the terminal helps to reduce the attack successful rate.

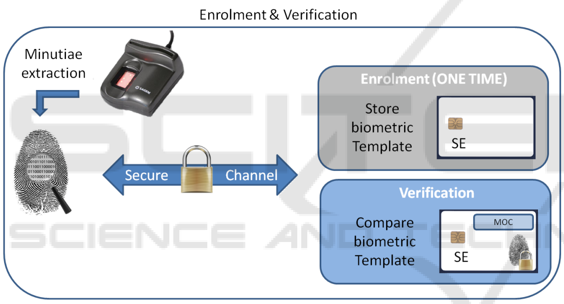


Figure 2: Explanation of an enroll en verification part on SE.

This paper is organized as follows. In the next section, we present the different works present on the state-of-the-art which permit to determine the fingerprint type. Section 3 is focused on the proposed methods based on minutiae template. Section 4 is devoted to the experimentation of fingerprint type recognition. Finally, we conclude and give some perspectives of this work.

2 RELATED WORKS

Many works have been done on the classification algorithms, such as healthcare (Kumar and Inbarani, 2016; Zhang et al., 2016; Park et al., 2016), network (Palmieri et al., 2013; Palmieri et al., 2014; Fiore et al., 2013) and imaging (Li et al., 2015; Alok et al., 2015; Elguebaly and Bouguila, 2015). On biometric field some works have been done for the processing of minutiae templates such as the orientation field reconstruction (Roy and Trivedi, 2014; Oehlmann et al., 2015), the matching algorithm (Jain and Pankanti, 2000; Kumar et al., 2014), the fingerprint protection (Jayaraman et al., 2014; Vigila et al., 2014). Few works have considered the ISO Compact Card II representation(Jain et al., 1999b; Zhang and Yan, 2004). All methods which permit to detect the fingerprint type are based on images and not on minutiae template. Different methods reconstruct the image with the minutiae template but need a lot of computation resources and time since a SE doesn't have enough resources to reconstruct images and compute these methods,the aim of the paper is to propose methods based only on minutiae template to determine the class of fingerprints.

3 FINGERPRINT CLASS RECOGNITION WITH ISO TEMPLATE

Our work is based on the minutiae template computed with ISO Compact Card II representation. 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 minutiae in the image (that is not available),
- T_i corresponds to the minutiae type (bifurcation, ridge ending ...),
- θ_i is the minutiae orientation (related to the ridge). Note that this information is represented by 6 bits (i.e. 64 different values).
- N_j is the number of minutiae for the sample j of the user.

Minutiae templates used in the experiments have been extracted using the NBIS tool, MINDTCT (Watson et al., 2007) from the NIST. From the ISO template we have generated a statistical vector named IsoStruct_{jk}. Consedering a whole template, for all minutiae we can construct four subsets considering 1) the x coordinate, 2) the y coordinate, 3) the ISO angle and 4)the minutiae type. From each subset, a normalized histogram was computed with fix value of bins. Then we obtain a IsoStruct_{jk} vector of size $3 \times N + 2$ by concatening these histograms, where N is the number of bins in the histograms computation and 2 is the histogram for the *Type* which contain only 2 values. This statistical vector IsoStruct_{jk} is defined as follows:

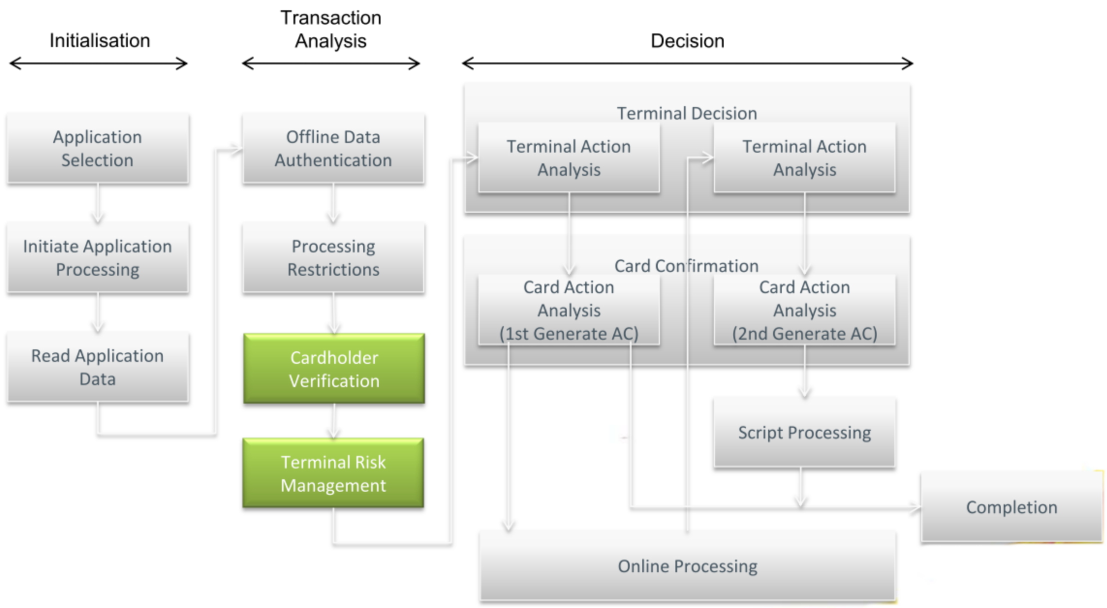


Figure 3: Flow of a complete EMV transaction.

$$\begin{aligned} \text{IsoStruct}_{jk} = \{&\text{HistoX}_{jk}, \\ &\text{HistoY}_{jk}, \text{HistoIsoAngle}_{jk}, \\ &\text{HistoType}_{jk}\} \end{aligned} \tag{1}$$

where $\text{HistoX}_{jk}, \text{HistoY}_{jk}, \text{HistoIsoAngle}_{jk}$ and HistoType_{jk} are normalized histograms. This histogram is generated with a variable number N of bins, mainly to refine the shape of the histogram.

With this statistical vector IsoStruct_{jk}, we want to determine the fingerprint class, and after determine which parameter is important for the fingerprint class recognition. For that purpose, we use a support vector machine (SVM) to create a model of each fingerprint class.

3.1 SVM Learning

From all existing classification schemes, a Support Vector Machine (SVM)-based technique has been selected due to high classification rates obtained in many previous works (Charrier et al., 2012; Hsu and Lin, 2002; Kudo and Sklansky, 2000), and to their high generalization abilities. The SVMs were developed by VAPNIK ET AL. (Vapnik, 1998) and are based on the structural risk minimization principle from statistical learning theory. SVMs express predictions in terms of a linear combination of kernel functions centered on a subset of the training data, known as support vectors (SV).

SVM being binary classifiers, several binary SVM classifiers are induced for a multi-class problem. A final decision is taken from the outputs of all binary SVM (Hsu and Lin, 2002).

The kernel function choice is critical for the design of a machine learning expert. Radial Basis Function (RBF) kernel function is commonly used with SVM. The most important reason is that RBF functions work like a similarity measure between two examples. A final decision must be taken from all binary decision functions. Many combination strategies can be used to obtain the final decision (Hsu and Lin, 2002). The majority vote is the usual way to do this.

3.2 Experimental Protocol

We list here all the elements to be defined to make experiments.

3.2.1 SFinge Databases

FVC databases do not provide any information on the fingerprint class. Nevertheless, it will be shown in different works (Maio et al., 2004; Fiérrez-Aguilar et al., 2005) than SFinge has the same behavior and similar performance than real databases. Hence, we may expect a similar performance of class recognition than real databases. We have generated five databases with the SFinge software, one for each class of fingerprint described in Table 1. Each SFinge database has 800 templates.

3.2.2 SVM Setup

We need to create a database for the training and one for the test. Multiple train-test sequences were run. In

Table 1: Fingerprint classes databases label.

Label	Fingerprint classes
1	Arch
2	Left Loop
3	Right Loop
4	Tented
5	Whorl

each, the fingerprint database was subdivided into distinct training and test sets. In each train-test sequence, 80% of the 5 SFinge database content was chosen for training, and the 20% for testing. Specifically, each training set contained 640 fingerprints, while each test set contained the 260 remaining fingerprints. 10 randomly chosen training and test sets were obtained and the class recognition rate was run over the 10 iterations. We have used the well known libsvm (Chang and Lin, 2011) with the default parameters.

3.3 Experimental Results

Here, we want to determine the number of bins needed to have the minimal impact on the recognition rate performance. We tested different values of bins (8, 16, 32 and 64) on the feature structure. We only consider the recognition results when 80% of the databases is used for learning for the four value of bins. Results are presented on Table 2.

Table 2: Table of Fingerprint class recognition with ISO template for all feature at 80% for learning.

Nbr_bins	Recognition rate on test db(%)
8	79.43
16	80.37
32	80.06
64	60.80

We can observe than the best results are obtained with 16 bins for the structure based feature. We can explain this result by the fact that the redundancy with 64 bins is high for this application. With only a features with 64 values ($50 = 3 \times 16 + 2$), we obtain 80.37% of fingerprint class recognition with the standard svm parameters (without any optimization). In the following, we keep this size of the feature vector.

The ISO template only contain four information, and we want to know which information is important for the fingerprint class recognition. The table 3 shows the recognition rate for each number of bins and for each paramter present in the ISO template. We can observe than the *Type* have the same recognition rate, this is due to the two possible values for this parameter, we only have an histogram with 2 bins in opposite with the other parameter. Concerning the X and Y we have bad results around 40%. In opposite, with ISO_Angle, we have the best recognition rate.

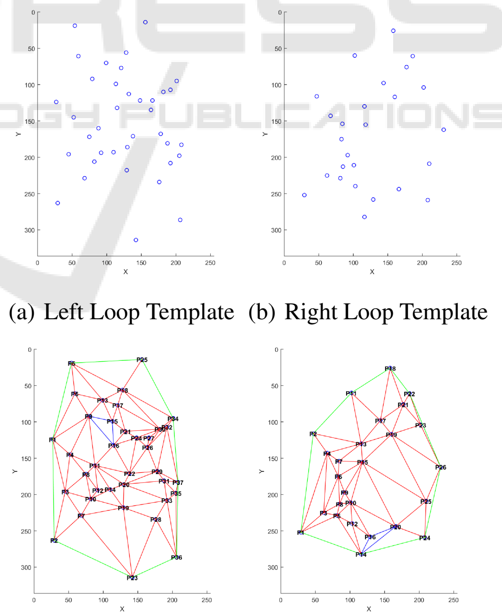
Table 3: ISO CC recognition rate for each element vs number of bins.

	Recognition rate (%)			
Nbr_bins	X	Y	ISO_Angle	Type
8	42.87	37.52	77.85	28.13
16	43.62	38.96	80.23	28.13
32	42.25	36.51	80.24	28.13
64	40.45	36.47	78.25	28.13

We can conclude than the ISO_Angle is an important information for the fingerprint class recognition. With around 79% of recognition rate, this is the most important parameter present in the initial template. It is a good result but we want to have more than one information to improve the fingerprint recognition rate.

4 NEW ATTRIBUTES SELECTION

As alluded above, using ISO templates, we have few information to characterize fingerprints.



(a) Left Loop Template (b) Right Loop Template

(c) Left Loop Triangulation (d) Right Loop Triangulation

Figure 4: Spatial fingerprint minutiae point and associated Delaunay triangulation.

As we can observed on both image 4(a) and image 4(b), we see that the spatial distribution of minuatiae differs. To take into account this observation, we modelize this difference using computational geometry approach. Amoung all existing schemes, we decided to use Delaunay triangulation (Aurenhammer, 1991; Su and Drysdale, 1995). Delaunay triangulation is used in various fields, such as computational geometry (Shewchuk, 2002) for resolving problems, or in surface reconstruction (Gopi et al., 2000; Labatut et al., 2007). In our case Delaunay triangulation allows to resolve the problem of translation and rotation of the ISO minutiae template and also allows us to make an abstraction of the minutiae space position. This yield us to create a structure containing parameters describing each template, as described in 4.1 and explained in Figure 5. These structure parameters are composed of elements such as shape, angles, area of the triangles, perimeter and so on.

4.1 Feature Structure for Each Template

For each template, we have computed the Delaunay triangulation-based on minutiae (Figure 6 shows an example of Triangulation).

For each obtained triangle, we extract different parameters:

- the three angles,
- the three edges lengths,
- the area.

To resume, the feature vector TriInf_{jk} is generated for the template j of the subject k and it consists of three main characteristics:

$$\begin{aligned}\text{TriInf}_{j,k} = \{&\{\text{AngleA}_{jkl}, \text{AngleB}_{jkl}, \text{AngleC}_{jkl}\},\\ &\{\text{LengthAB}_{jkl}, \text{LengthAC}_{jkl}, \text{LengthBC}_{jkl}\},\\ &\{\text{Area}_{jkl}\}\}, \forall l \in [1; M_j],\end{aligned} \tag{2}$$

where $\{\text{AngleA}_{jkl}, \text{AngleB}_{jkl}, \text{Angle C}_{jkl}\}$ is the vector of data related to angle values of the M_j triangles of the template j, $\{\text{LengthAB}_{jkl}, \text{LengthAC}_{jkl}, \text{LengthBC}_{jkl}\}$ represents the vector of data related to computed lengths for the M_j triangles of the template j, $\{\text{Area}_{jkl}\}$ corresponds to the vector of data related to the area of the M_j triangles of the template j.

We also add parameter not related to the Delaunay triangulation but issues of the original template:

- Minutiae orientation.

$$\begin{aligned}\text{IsoAngleInf}_{j,k} = \{&\{\text{Orientation}_{jki}\}\\ &\}, \forall i \in [1; N_j],\end{aligned} \tag{3}$$

where Orientation_{jki} represents the vector data containing the ISO angle of the N_j minutiae of the template j.

4.2 Feature Probability Density

From this two feature vector (TriInf_{jk} and IsoAngleInfo_{jk}), a new and statistical vector is generated. We compute a normalized histogram to approximate a probability density for each feature which is not dependent to the number of minutiae in the template. These histograms are computed considering a fix value of bins. Then, we obtain a $\text{TemplateStruct}_{jk}$ vector of size $4 \times N$, where N is the number of bins in the histograms computation, by concatening these histograms.

This statistical vector $\text{TemplateStruct}_{jk}$ is defined as follows:

$$\begin{aligned}\text{TemplateStruct}_{jk} = \{&\text{HistoAngle}_{jk},\\ &\text{HistoDistance}_{jk}, \text{HistoArea}_{jk},\\ &\text{HistoISOAngle}_{jk}\}\end{aligned} \tag{4}$$

where $\text{HistoAngle}_{jk}, \text{HistoDistance}_{jk}, \text{HistoArea}_{jk}$ and $\text{HistoISOAngle}_{jk}$ are normalized histograms computed from their associated subvector of TriInf_{jk} and IsoAngleInfo_{jk}. Those histograms are generated with a variable number N of bins, mainly to refine the shape of the histogram.

4.3 Fingerprint Class Recognition Results

We have used the same protocol as defined in Section 3.2 and the number of bins defined in Section 3.3 with $N = 16$.

The Table 4 gives the recognition results for the new attributs selection.

Table 4: Fingerprint class recognition results for the new attributs selection with 80% of learning.

	Recognition rate (%)
ISO method	80.37
Proposed method	89.12

If we compare the results between only the ISO template prensented in and the new feature, we have a difference around 10%. The new feature present a better fingerprint recognition rate with 89% of good fingerprint class recognition.

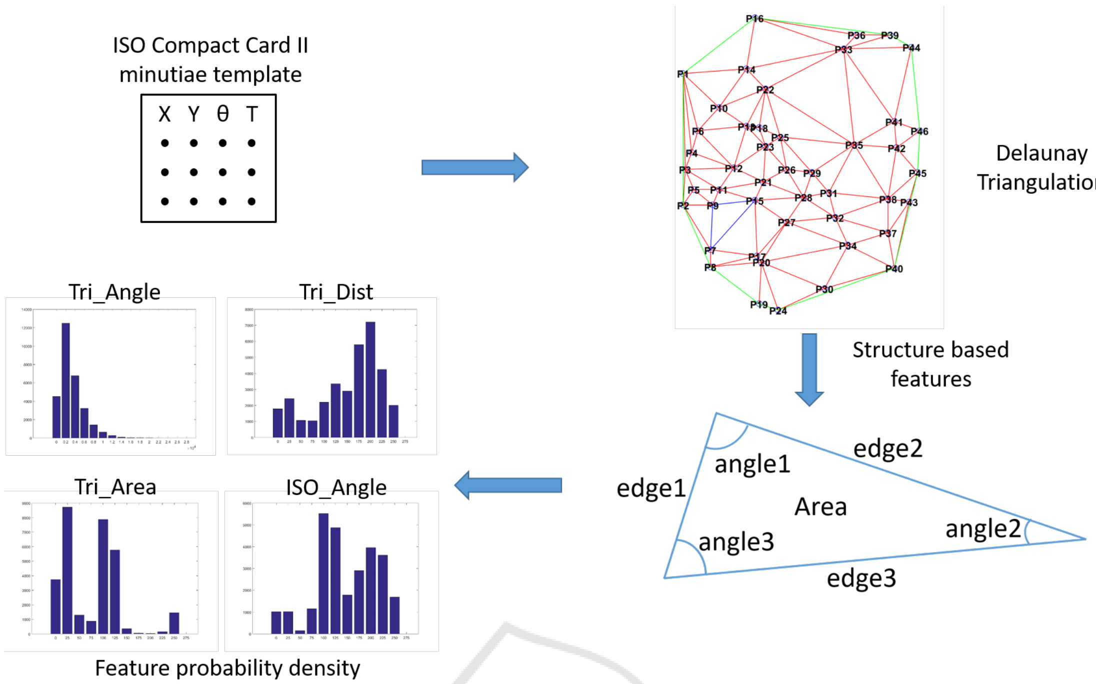


Figure 5: General scheme for the Attribute vector.

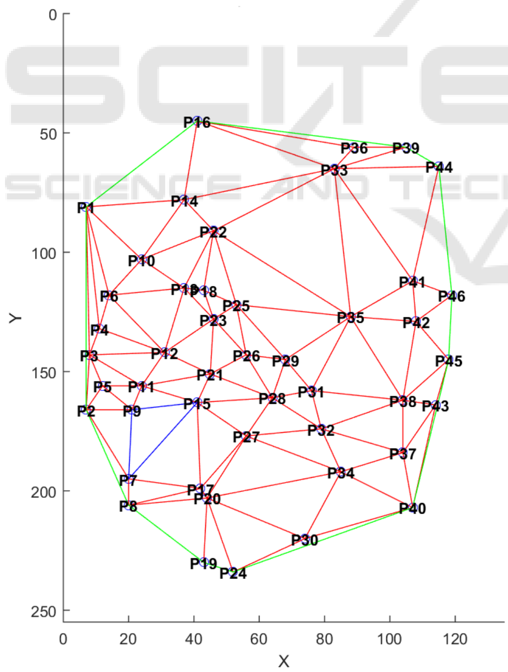


Figure 6: Delaunay Triangulation for one ISO Compact Card II template.

5 DISCUSSION

Our problematic is to determine the fingerprint class only with the ISO template informations. We create a vector containing histogram for each parameter of the ISO template. With this vector we obtain 80.37% of recognition rate, but we have seen than the ISO_Angle is the parameter which permit to obtain a good recognition rate alone 80.23%. This is why we proposed a geometric approach based on the Delaunay triangulation to obtain more parameters and also keep the ISO_Angle. With this approach, we increase by 9% the recognition rate and we obtain 89%. From comparison, Jain *et al.* (Jain et al., 1999a) have developed a method of fingerprint class recognition based on the image and get a recognition rate of 90%. Our approach is nearest the recognition rate based on image, this shows that the approach restraint is promising.

6 CONCLUSION AND PERSPECTIVES

In this paper, we proposed two fingerprint class recognition approach based only on ISO template with no access on images or reconstructed images. We have first of all determined the number of bins needed for our statistical approach. After, we have determined than ISO_Angle parameter issued from the ISO template is important for the fingerprint recognition rate. We have proposed a new feature which permit to have more than one information to determine the fingerprint class. With this method we obtain 89% of fingerprint class recognition rate in comparaison with 80% for the ISO template. We have improved the recognition rate around 10%. In our case of study, an EMV transaction, we have two approach and we have to choose between more computation time, ressources but 89% of recognition rate and few ressources and quicker approach based on ISO template but only with 80% of fingerprint class recognition. We have shown when one adds fingerprint recognition module, both on smartcard and Point of sales we help to secure EMV transaction when biometric is taking into account.

As perspectives, we plan to improve these recognition rates of the fingerprint class by using other features. And also to test in real condition on SE these approach.

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