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A Preliminary Study on Fingerprint Classification Using Fuzzy Rule-based Classification Systems

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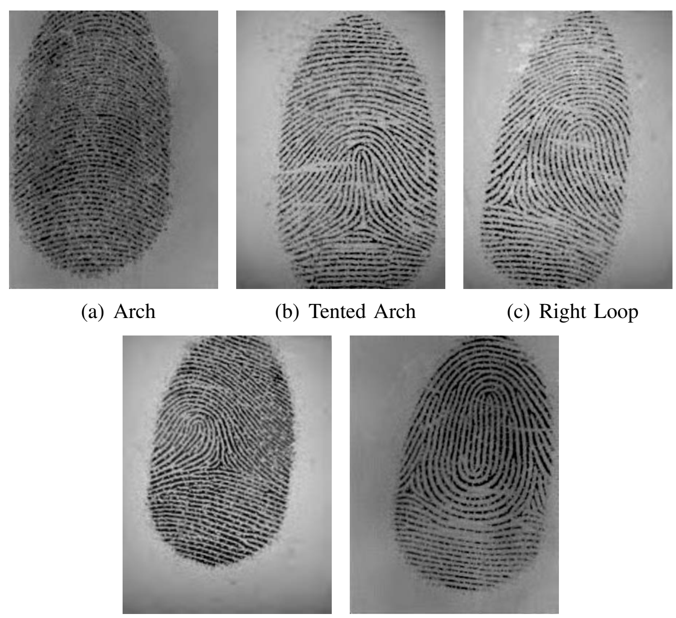
***Abstract*—In this work we analyze the competitiveness of fuzzy rule-based systems in comparison with black box models like support vector machines to deal with fingerprint classification problems. With this aim, we carry out an experimental study applying different feature extraction models (covering almost every kind of features that are usually considered in this problem) and three fingerprint databases of different qualities. The obtained results show the good behavior of fuzzy rule-based classification systems. Observing these results, new future lines are outlined, which could improve the classification performance achieved with the current models.**

I. Introduction

Fingerprint recognition systems are the most widespread bio-metric authentication systems. A fingerprint can be defined as the pattern formed by the valleys and ridges in the surface of the fingertips. The individuality of the fingerprints is given by the local characteristics of the ridges and the relationships among them [1]. Among all these possible characteristics, minutiae are the most widely used when carrying out the matching between fingerprints, i.e., deciding whether two fingerprints belong to the same person or not [2].

There are two types of fingerprint recognition systems. Verification systems aims to verify whether the identity claimed by a person is true or it is false. Otherwise, the goal of identification systems is to identify the person in the database to which the input fingerprint belongs to (or detecting if the fingerprint does not belong to any person), which is a much more difficult and complex problem. One of the main problems in fingerprint identification systems is the computational cost, since each input fingerprint needs to be compared with all the fingerprints stored in the system. For this reason, time reduction in the matching process is a key factor in systems having huge databases. On this account, a commonly considered solution to decrease the amount of time spent in the matching process consists in splitting the whole database in several databases composed of a lower number of fingerprints sharing certain global features [3]. In this manner, the matching process for a new input fingerprint is only carried out against those fingerprints in the database whose fingerprints share the same global features. This problem is known as the fingerprint classification problem.

The most common classification approach was given by Henry [4]. He defined five major fingerprint classes, which are the ones that are commonly used in the specialized literature: *left-loop, right-loop, whorl, arch and tented-arch* [3] (Fig. 1). These fingerprint classes are unevenly distributed in the population (3.7%, 2.9%, 33.1%, 33.8% and 27.9%, respectively), which increases the difficulty of the classification problem from the machine learning point of view [5]. Obviously, the classification in an authentication system has to be reliable, since it has a direct impact in the subsequent matching process, because a misclassification may lead to a false identification in the matching process or to a significant increase in the penetration rate, which is defined as the percentage of the fingerprints in the database that are compared with the input fingerprint.



(a) Arch (b) Tented Arch (c) Right Loop

(d) Left Loop (e) Whorl

Fig. 1. The five major classes defined by Henry [4] considered in the fingerprint classification problem.

In the specialized literature there are a lot of methods to tackle the fingerprint classification problem [3]. In fingerprint classification there are two well-differentiated stages:

- *Feature extraction:* It is the process of extracting a set of meaningful global features of the fingerprint for the classification stage.
- *Classification:* It is the process that, using the features

extracted in the feature extraction stage, classifies each fingerprint in one out of the five possible classes of fingerprints. To do so, learning algorithms are usually applied to build a classifier able to assign the class label to each fingerprint depending on the features extracted [6], although there exist some approaches in which fixed classification models have been proposed [7], which generally provide poorer results.

In this work we consider three different feature extraction models. The first one makes use of the feature set denoted as FingerCode [6]. The second one [8] also uses the FingerCode but it adds information based on the singular points of the fingerprint. The singular points are the areas of the fingerprints in which the orientations of the ridges vary more abruptly. There are two types of singular points known as *cores* and *deltas* [3]. The last method only considers information obtained from the singular points and it uses features obtained from the relationships that are present among the already mentioned points [9]. These approaches are some of the most relevant and more accurate methods defined in the specialized literature. Moreover, the authors provided enough information to carry out their implementation, which is not very common in fingerprint classification literature.

Once we have selected the feature extraction methods, we focus on the classification and learning stage. Our purpose is to analyze different fuzzy rule learning methods with the objective of investigating whether those fuzzy classifiers are able to provide an accuracy rate as good as that achieved by other classifiers that are commonly used in this problem, like Support Vector Machines (SVMs) [10].

Fuzzy Rule-Based Classification Systems (FRBCSs) [11] are widely applied to address classification problems because they generate an interpretable model, since the antecedents of the fuzzy rules are composed of linguistic terms. However, it is usually claimed that they are not as accurate as other non-interpretable models such as SVMs. In this work we want to develop a preliminary study about fingerprint classification using fuzzy techniques, with the goal of showing that they can be as competitive as SVMs when facing the fingerprint classification problem despite being interpretable classifiers. With this aim, we consider three state-of-the-art fuzzy classifiers like FARC-HD [11], IVTURS [12] and FURIA [13].

In order to carry out this study, we have used the SFinGe tool[1] [3], [14] to generate three databases composed of 10000 fingerprints of different qualities. The SFinGe software allows us to create synthetic fingerprints that are similar to the real ones and whose main advantage is the fact that the class label can be easily codified. Furthermore, we consider the three aforementioned feature extraction methods and we analyze the behavior of the classifiers considered in all of them. In addition to the three FRBCSs, we consider two classical methods for comparison purposes: the C4.5 decision tree [15] and SVMs with two different configurations.

The remainder of the work is as follows. In Section II we describe the three considered feature extraction methods. Next, we introduce the classifiers used in the experimental study in Section III. The experimental framework is described in Section IV, whereas the obtained results along with the corresponding analysis are presented in Section V. Finally, Section VI concludes the work.

II. Feature Extraction Methods of Fingerprints

In this section, we briefly describe the feature extraction methods that we have considered to perform the experimental study. We must point out that these three methods cover almost every type of the usually considered features for the fingerprint classification problem [3]. Furthermore, they are state-of-the-art methods that usually obtain accurate results.

A. FingerCode (JAIN)

Jain's method [6] uses a global representation of the ridge flow in the fingerprint, which has the suitable property of being invariant to the presence of minutiae. In order to obtain this representation, in first place the Poincarè method [3] is used to find out the core (or reference point) of the fingerprint, which is the area with the largest amount of information for the classification stage. In the case that no core is found, an estimation based on the co-variances of the orientations is applied so as to seek for a reference point.

The area defined around the core (or the reference point) is later decomposed into four components using the Gabor filter with different orientations. The application of this filter produces that both valleys and ridges in the corresponding orientation in each component become clearly defined, whereas valleys and ridges with other local orientations disappear. In such a way, the well-defined areas (ridges and valleys in the same orientation as that of the Gabor filter) have a large variation of the grey level, whereas the opposite effect occurs in the other areas.

From these decomposed fingerprint image the final features for the classification step are extracted. In order to do so, each component is divided into small blocks, whose standard deviation of the grey levels in the pixels in the block is computed. These values are the ones that form the feature vector proposed by Jain, which is commonly known as FingerCode. The model proposed by Jain considers forty-eight blocks in each of the four mentioned components, which implies that the feature vector is composed of one hundred and ninety-two values that represent the response degree of each block to each orientation of the corresponding filter.

B. FingerCode and Singular Points (HONG)

Hong's method [8] is an extension of the method proposed by Jain. The authors consider the usage of the FingerCode (without any change with respect to the original one proposed by Jain), but they also consider new information based on the singular points of the fingerprint to be classified. In order to add this new information, the singular points are obtained using the Poincarè method. Besides the number and the location of this points, other measures obtained from the pseudo-ridges are considered. Pseudo-ridges start from the singular points and aim to follow the global ridge flow, which produce useful information for classification purposes.

As a result, ten new features are added to the one hundred and ninety-two that compose the FingerCode, which makes a

[1] Synthetic Fingerprint Generator: http://biolab.csr.unibo.it/research.asp?organize=Activities&select=&selObj=12&pathSubj=111||12&

total of two hundred and two features in the Hong's method. Among the new ten features the number of cores and deltas, their locations and relative distances of the deltas and the end points of the pseudo-ridges with respect to the main core can be found.

C. Singular Points (LIU)

Liu's method [9] directly extracts a number of features from the singular points of the fingerprint. These features are mainly relative measures to those singular points and the confidence obtained in their detection. This confidence can be estimated because the method applied for their detection uses complex filters instead of the Poincarè method as it is commonly done.

The complex filters allow one to represent the symmetries that are present in the areas in which the singular points are located in the orientation maps [3] (we recall that it represents the local flow of the ridges in each area of the firngerprint) by means of complex numbers. Once the filters are defined, the convolution with the complex representation of the orientation map is carried out. In this manner, the areas where singular points are present provide a larger responses to the filter. These responses allow the detection of the singular points using a predefined threshold in the detection process.

Furthermore, with the aim of improving the detection of both the singular points and the obtained features, the Liu's method makes use of a multi-scale model of the orientation map. In each scale, the same features are extracted based on the singular points detected, which makes the algorithm more robust. More specifically, sixteen features are obtained in each scale; hence, the final feature vector is composed of sixty-four features because the recommended configuration considers four different scales.

III. CLASSIFIERS

In this section, we will recall the main points of the five classifiers considered to face up to the fingerprint classification problem.

A. C4.5 Decision Tree

C4.5 [15] is a decision tree generation algorithm. The decision tree is built using a top-down methodology applying the normalized information gain (difference in entropy) that is obtained when selecting a feature to split the example space of the next node. The feature having the maximum normalized information gain is the one selected to generate the branches of the node (to make the decision).

B. FARC-HD

FARC-HD [16], which stands for *Fuzzy Association Rule-based Classification model for High-Dimensional problems*, is a fuzzy association rule-based classifier that provides a compact and accurate set of fuzzy rules. To generate the knowledge base this method applies the following three steps:

- *Generation of the fuzzy rules*: for each class a search tree to obtain the frequent itemsets using the support and the confidence of the considered items is applied. In this classifier the items are the linguistic labels. Therefore, the fuzzy rules are created from the obtained frequent itemsets.
- *Selection of the most interesting fuzzy rules*: in the first step of the generation algorithm a huge number of fuzzy rules can be created. For this reason, the most interesting fuzzy rules of each class are selected using a strategy of weighted examples. The weight of each example is measured based on the covering degree of the selected fuzzy rules.
- *Lateral tuning and rule selection*: the last step of the method consists in applying an evolutionary algorithm to select the set of rules along with the best lateral position of the fuzzy sets (used to model the linguistic labels) that provides the best performance.

C. IVTURS

IVTURS [12], which stands for *Interval-Valued fuzzy rule-based classification system with TUning and Rule Selection*, is a modification of FARC-HD in which interval-valued fuzzy sets are considered. More specifically, the modifications introduced in IVTURS with respect the original FARC-HD algorithm are as follows:

- This method represents the linguistic labels using interval-valued fuzzy sets instead of fuzzy sets. In this manner, the ignorance degree [17] associated with the assignment of a number as the membership degree of the elements to the fuzzy set is modeled.
- An extension of the fuzzy reasoning method to deal with interval information, instead of with numeric information, throughout the inference process.
- It substitutes the tuning of the lateral position of the linguistic labels by the tuning of the values introduced in the first step of the interval-valued fuzzy reasoning method.

D. FURIA

FURIA [13], which stands for *Fuzzy Unordered Rule Induction Algorithm*, is an algorithm that constructs the model based on the RIPPER algorithm [18] and introduces the following modifications:

- It changes the representation of the rules because it generates fuzzy rules instead of conventional crisp rules.
- The use of the default rule (this rules classifies the examples in the majority class) is removed because it generates a set of rules for each class. In this manner, the ordering of the rules is irrelevant.
- It does not apply the pruning method in the rule learning process.
- A local method for the modification of the rules is added in order to classify those examples that do not fire none of the fuzzy rules generated.

E. Support Vector Machines

Support Vector Machines (SVMs) [10] attempt to map the original input space into a high dimensional space by means of a kernel function, which is used to avoid the computation of the internal product between two vectors. In the new feature space, they determine the optimal hyper-plane to make the differentiation between the classes of the problem, which is the one having the largest margin between the classes. In this manner, the empirical risk instead of the expected risk is minimized. SVMs are widely used due to their high accuracy but they do not provide an interpretable model.

IV. Experimental Framework

In this section we present the experimental framework used to develop the experimental study and consequently, to obtain the results which are shown in Section V.

In order to carry out the experimental study we have considered three fingerprint image databases of different qualities. These databases have been generated using the SFinGe software tool [3], [14], which allows one to generate synthetic fingerprints having a realistic appearance with different quality levels (translations, rotations and geometric deformations). Moreover, this tool allows us to obtain the class label assigned to each fingerprint so that the performance of the classifiers can be easily evaluated.

Afterwards, we describe the three quality profiles of fingerprints we have considered for the generation of the databases with the SFinGe tool:

- *High Quality No Perturbations* (HQNoPert): Fingerprints are generated with high quality without any kind of perturbation performed on the fingerprint.
- *Default*: The fingerprints generated are of middle quality with slight localization and rotation perturbations.
- *Varying Quality and Perturbations* (VQandPert): The fingerprint database is composed of fingerprints captions of varying qualities. Furthermore, these fingerprints receive a perturbation treatment in which location, rotation and geometric distortions are applied to the fingerprints.

For each profile, we have generated five databases, which are composed of 2000 fingerprints, that allow us to obtain 10000 fingerprints for each quality level. Therefore, a total of 30000 fingerprints are used to check the behavior of the classifiers. We must point out that fingerprints have been generated following the natural distribution of the classes. In order to speed up the experiments, instead of applying a 5 folder cross validation model we have considered another scheme in which each database of 2000 fingerprints is used as test folder for the previous training database of 2000 fingerprints. That is, to test the results on the database number two we use the database number one as training database and when this latter database is used as testing database we use the database number five as training database.

As we have already mentioned, the fingerprint classification problem is divided into two steps. In the first one, the feature extraction is carried out, obtaining the features that will represent each fingerprint and will be used for classification. In the case of two out of the three feature extraction methods considered in this study (Jain and Hong, that is, those based on FingerCode) a fingerprint can be rejected in the feature extraction step. As a result, it is neither considered in the classification process, since no features are available to perform the classification. The rejection process depends on the localization of the core or reference point. A fingerprint is rejected whenever any part of the area used to extract the FingerCode fall out of the fingerprint image. On this account, these fingerprints are deleted from the corresponding databases. Likewise, we have also deleted these fingerprints from the databases when Liu's method is applied in order to be able to compare the feature extraction methods among themselves. Hereafter we show the percentage of fingerprints that were deleted from the databases (rejection rate) for the different quality levels considered. Obviously, the ratio increases as the quality level decrease.

- HQNoPert: 1.44%.
- Default: 5.38%.
- VQandPert: 15.90%.

Hence, the results reported in the next section in term of accuracy rate do not take into account the fingerprints that were eliminated from the database due to the impossibility of extracting their features.

Regarding the classifiers considered, we should notice that due to both the high dimension and the amount of examples in the databases, the direct application of FARC-HD and IVTURS becomes almost impossible. For this reason, we have considered the features used by the $C4.5$ decision tree in the decision tree generation process as a kind of preliminary feature selection method. As a result, we obtain a database having a lower number of features for the learning process of both FARC-HD and IVTURS methods. In the case of the remainder methods (FURIA, SVMs), the original databases (with all the features) are used in the learning phase in order to carry out a faithful comparison with respect the capabilities of each classifier. In these methods, the feature selection process can be restrictive, hindering the results obtained. In fact, preliminary experiments showed us that carrying out this feature selection (using the features of $C4.5$) and using the datasets with fewer features lead to worse results in the case of FURIA and SVMs. On this account, we only show the results obtained considering all the features in these algorithms which are capable of dealing with such a large number of features.

Finally, the configurations of the classifiers considered in the study are shown in Table I. We must point out that we have applied two different configurations in the case of SVMs. The first one uses a polynomial kernel (SVM_{Pol}) whereas the second one uses a radial basis kernel (SVM_{RBF}).

V. Experimental study

The classification results obtained in the testing databases for each one of the three feature extraction methods and the five classifiers are shown in Tables II, III and IV. The results are measured using the accuracy rate obtained over the databases (the fingerprints rejected by the feature extraction methods are not taken into account). Each Table represents the obtained results for each quality profile, that is, the high quality database

TABLE I. SET-UP OF THE PARAMETERS OF THE CLASSIFIERS.

Algorithm	*Parameters*
C4.5	Pruning: true, Confidence level: 0.25 Minimum number of examples per leaf: 2
FARC-HD and IVTURS	Number of linguistic labels per variable: 5 Minimum Support: 0.05 Minimum Confidence: 0.8, Maximum depth: 3 Parameter k: 2, Evaluations: 20000 Number of individuals: 50, α parameter: 0.02 Bits per gen: 30 Inference: Additive Combination
FURIA	Number of optimizations: 2 Number of linguistic labels per variable: 3
SVMs	C: 1.0, Tolerance: 0.001, ϵ: 1.0E-12 RBFKernel$_\gamma$: 0.01, Logistic Model: True

without perturbations (HQNoPert) in Table II, the database having the default quality (Default) in Table III and variable quality with perturbations (VQandPert) in Table IV. These Tables are also split in three sections, one for each feature extraction method, and for each one of the three methods we show the results obtained with the five classifiers considered in this study. The best results for each feature extraction method are highlighted in **bold-face**.

TABLE II. RESULTS OBTAINED IN TESTING USING THE HQNOPERT DATABASE AND THE THREE FEATURE EXTRACTION METHODS STUDIED.

Features	Database	C4.5	FARC-HD	FURIA	IVTURS	SVM_{Pol}	SVM_{RBF}
Jain	1	92.09	94.53	93.56	94.02	**95.64**	95.08
	2	90.48	93.69	93.69	93.84	95.62	**95.73**
	3	92.12	92.93	93.43	93.68	**96.01**	95.00
	4	92.69	94.31	94.31	93.91	**96.45**	95.89
	5	91.52	93.40	92.79	93.40	**95.12**	94.06
	Mean	91.78	93.77	93.56	93.77	**95.77**	95.15
Hong	1	95.54	95.74	94.93	95.64	**96.45**	95.89
	2	95.27	96.54	95.57	96.08	95.93	**97.30**
	3	94.19	95.30	95.50	95.35	95.40	**96.46**
	4	94.37	96.45	95.99	96.55	96.90	**97.16**
	5	95.33	**96.60**	95.23	95.99	95.58	96.55
	Mean	94.94	96.13	95.44	95.92	96.05	**96.67**
Liu	1	**94.78**	93.92	94.17	94.02	93.72	89.25
	2	94.76	94.61	**95.17**	94.10	94.40	89.92
	3	**94.80**	93.89	**94.80**	93.73	94.34	93.89
	4	94.67	94.21	**95.63**	94.52	94.97	93.96
	5	93.80	93.65	93.75	93.40	**93.91**	92.48
	Mean	94.56	94.05	**94.70**	93.95	94.27	91.90

Looking at the obtained results we must stress the following facts.

- Fuzzy methods obtain competitive results when Liu's method is used to extract the features of the fingerprints. This can be due to the fact that the use of fuzzy rules makes sense when the relationships produced among singular points are considered whereas fuzzy rules are more difficult to be learned from the FingerCode (for example, methods based on fixed rules generally considered singular points [7]). We have to stress that when addressing the most difficult database (VQandPert) the synergy between fuzzy rules and Liu's method allows the results of SVMs to be enhanced. Among all the fuzzy methods, the behavior of FURIA must be highlighted, which provides the best result in all the databases.

TABLE III. RESULTS OBTAINED IN TESTING USING THE DEFAULT DATABASE AND THE THREE FEATURE EXTRACTION METHODS STUDIED.

Features	Database	C4.5	FARC-HD	FURIA	IVTURS	SVM_{Pol}	SVM_{RBF}
Jain	1	89.25	91.78	92.31	91.25	**94.20**	94.10
	2	89.78	92.22	90.95	91.69	**94.76**	94.02
	3	89.60	91.72	92.25	91.62	94.43	**95.07**
	4	91.48	92.91	92.65	93.12	94.97	**95.08**
	5	90.00	91.89	91.95	91.84	**94.00**	93.58
	Mean	90.02	92.11	92.02	91.90	**94.47**	94.37
Hong	1	93.05	93.78	93.15	93.99	**95.05**	94.84
	2	92.48	93.70	92.69	93.44	95.24	**95.29**
	3	92.94	93.90	94.01	94.16	95.86	**96.07**
	4	92.80	94.13	94.60	95.71	95.93	**96.08**
	5	92.53	93.95	93.95	94.11	**95.11**	94.84
	Mean	92.76	93.89	93.68	94.28	**95.44**	95.43
Liu	1	92.83	**93.52**	93.41	86.67	93.10	90.20
	2	93.01	93.49	**93.91**	93.12	93.01	92.91
	3	93.42	93.53	**94.27**	93.00	93.47	92.63
	4	93.86	**94.55**	94.44	93.70	94.50	92.38
	5	**94.47**	93.79	94.37	93.58	93.42	92.11
	Mean	93.52	93.78	**94.08**	92.01	93.50	92.04

TABLE IV. RESULTS OBTAINED IN TESTING USING THE VQANDPERT DATABASE AND THE THREE FEATURE EXTRACTION METHODS STUDIED.

Features	Database	C4.5	FARC-HD	FURIA	IVTURS	SVM_{Pol}	SVM_{RBF}
Jain	1	86.36	90.94	90.30	90.94	92.45	**92.56**
	2	84.72	87.36	86.40	85.68	**90.79**	88.87
	3	84.21	87.11	87.35	86.98	**90.99**	89.64
	4	83.38	86.85	87.10	88.50	89.59	**90.14**
	5	82.69	86.99	86.80	88.50	**89.56**	89.50
	Mean	84.27	87.85	87.59	88.12	**90.68**	90.14
Hong	1	87.87	93.21	92.51	93.37	93.32	**94.12**
	2	88.21	88.69	89.17	88.69	**91.64**	89.95
	3	87.05	89.02	88.40	88.96	**90.44**	90.38
	4	84.97	88.50	88.80	89.47	**91.54**	90.87
	5	84.65	89.01	88.21	89.01	90.12	**90.55**
	Mean	86.55	89.68	89.42	89.90	**91.41**	91.17
Liu	1	92.29	91.91	**92.83**	92.13	91.54	88.79
	2	90.43	90.67	**91.16**	89.59	89.83	88.51
	3	88.96	89.45	**91.30**	89.57	89.27	87.17
	4	90.44	90.69	**91.48**	89.29	88.68	88.07
	5	89.93	90.12	**90.79**	89.93	89.20	87.78
	Mean	90.41	90.57	**91.51**	90.10	89.70	88.06

- Similarly, the feature extraction methods proposed by Jain and Hong work generally better with SVMs. Anyway, FRBCSs are not far from the results obtained with SVMs when Hong's method is considered (the most accurate). More specifically, the difference is only around 1% in the HQNoPert database and around 2% in the other two databases.

- The behavior of the $C4.5$ decision tree obtains worse results than fuzzy classifiers when it deals with problems having a huge number of features like the feature extraction methods of Jain and Hong. In the case of Liu's method, the differences are not as large as with the other feature extraction methods, but without achieving the accuracy of FRBCs in most of the cases.

- FARC-HD and IVTURS are competitive with respect to FURIA when we use the feature extraction methods of Jain and Hong, whereas their performance is slightly worse when using Liu's method (but in this case they provide better results than SVMs). We must recall that, with both Jain's and Hong's feature extraction methods, FARC-HD and IVTURS only consider those features used in the learning step of the $C4.5$ decision tree, which is always improved by both classifiers using the same features. For this reason, it seems reasonable to think that both classifiers along with a state-of-the-art feature selection method might reach very competitive results with respect to SVMs.
- The synergy between Liu's feature extraction method and FURIA is remarkable. FURIA is always the algorithm achieving the best result with Liu's method, but also their combination stands out when the quality of the database worsen, being the best combination in the most difficult database (VQandPert).
- Analyzing the feature extraction methods, Hong allows to obtain better results (as it was expected) than Jain in all databases and classifiers, since it adds complementary information to the one contained in the database generated by the Jain's method. Regarding Liu's method, which only uses the information of the singular points, its competitive behavior is remarkable, although with the easiest databases it does not achieve as accurate results as those obtained with Hong's or Jain's methods and SVMs. Otherwise, it reaches the best results with the most difficult database, hence, it can be concluded that Liu's method is more robust against quality than Hong's and Jain's ones.

Finally, it is worth noting the fact that SVMs make use of a One-Versus-One model (OVO) [19] to tackle the multi-class classification problem. This scheme usually allows one to improve the results obtained in multi-class classification problems. Although in the case of using SVMs there are not more options to face multi-class classification problems, the usage of an OVO strategy could also be applied for the remainder methods, whose usage is non-necessary because they allow to directly address these problems. For this reason, in order to improve the accuracy of these models a possible solution would be to address the fingerprint classification problem decomposing the original problem into easier to solve binary problems. This solution along with an appropriate feature selection method may lead to obtaining really competitive results versus black box models such as SVMs.

VI. Conclusions

In this work we have carried out a preliminary study to address fingerprint classification problems using FRBCSs. In order to do so, we have considered fingerprint databases of three different qualities and three feature extraction methods, which have been tested using three state-of-the-art fuzzy classifiers and two classical methods.

The results obtained allow us to stress the competitiveness of FRBCSs in terms of accuracy in the fingerprint classification problem. We have also pointed out two important future lines of work: the usage of a more powerful feature selection method (instead of considering those features used by C4.5) and the decomposition of the multi-class classification problem using the OVO strategy. Another option is the analysis of the combination of features coming from different feature extraction methods, aiming to emphasize the advantages of the different methods.

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References

[1] L. Hong, Y. Wan, and A. Jain, "Fingerprint image enhancement: algorithm and performance evaluation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, pp. 777–789, 1998.

[2] R. Cappelli, M. Ferrara, and D. Maltoni, "Minutia cylinder-code: A new representation and matching technique for fingerprint recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 12, pp. 2128–2141, 2010.

[3] D. Maltoni, D. Maio, A. Jain, and S. Prabhakar, *Handbook of fingerprint recognition*. Springer-Verlag New York Inc, 2009.

[4] E. Henry, *Classification and Uses of Finger Prints*. Routledge, London, 1900.

[5] M. Galar, A. Fernández, E. Barrenechea, H. Bustince, and F. Herrera, "A review on ensembles for the class imbalance problem: Bagging-, boosting-, and hybrid-based approaches," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 42, no. 4, pp. 463–484, 2012.

[6] A. K. Jain, S. Prabhakar, and L. Hong, "A multichannel approach to fingerprint classification," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 4, pp. 348–359, 1999.

[7] K. Karu and A. K. Jain, "Fingerprint classification," *Pattern Recognition*, vol. 29, no. 3, pp. 389–404, 1996.

[8] J.-H. Hong, J.-K. Min, U.-K. Cho, S.-B. Cho, and C. H. Leung, "Fingerprint classification using one-vs-all support vector machines dynamically ordered with naive bayes classifiers," *Pattern Recognition*, vol. 41, pp. 662–671, 2008.

[9] M. Liu, "Fingerprint classification based on adaboost learning from singularity features," *Pattern Recognition*, vol. 43, no. 3, pp. 1062–1070, 2010.

[10] V. Vapnik, *Statistical Learning Theory*. New York: Wiley, 1998.

[11] J. Alcalá-Fdez, A. Fernández, J. Luengo, J. Derrac, S. García, L. Sánchez, and F. Herrera, "KEEL data-mining software tool: Data set repository, integration of algorithms and experimental analysis framework," *Journal of Multiple-Valued Logic and Soft Computing*, vol. 17, no. 2–3, pp. 255–287, 2011.

[12] J. A. Sanz, A. Fernandez, H. Bustince, and F. Herrera, "IVTURS: A linguistic fuzzy rule-based classification system based on a new interval-valued fuzzy reasoning method with tuning and rule selection," *IEEE Transactions on Fuzzy Systems*, vol. 21, no. 3, pp. 399–411, 2013.

[13] J. Hühn and E. Hüllermeier, "FURIA: an algorithm for unordered fuzzy rule induction," *Data Mining and Knowledge Discovery*, vol. 19, no. 3, pp. 293–319, 2009.

[14] R. Cappelli, D. Maio, and D. Maltoni, "Sfinge: an approach to synthetic fingerprint generation," in *Eighth International Conference on Control, Automation, Robotics and Vision (ICARCV2004)*, Kunming, China, December 2004.

[15] J. R. Quinlan, *C4.5: Programs for Machine Learning*, 1st ed. San Mateo-California: Morgan Kaufmann Publishers, 1993.

[16] J. Alcala-Fdez, R. Alcala, and F. Herrera, "A fuzzy association rule-based classification model for high-dimensional problems with genetic rule selection and lateral tuning," *IEEE Transactions on Fuzzy Systems*, vol. 19, no. 5, pp. 857–872, 2011.

[17] J. Sanz, A. Fernández, H. Bustince, and F. Herrera, "A genetic tuning to improve the performance of fuzzy rule-based classification systems with interval-valued fuzzy sets: Degree of ignorance and lateral position," *International Journal of Approximate Reasoning*, vol. 52, no. 6, pp. 751–766, 2011.

[18] W. W. Cohen, "Fast effective rule induction," in *Proceedings of the 12th international conference on Machine learning*, 1995, lake Tahoe, CA.

[19] M. Galar, A. Fernández, E. Barrenechea, H. Bustince, and F. Herrera, "An overview of ensemble methods for binary classifiers in multi-class problems: Experimental study on one-vs-one and one-vs-all schemes," *Pattern Recognition*, vol. 44, no. 8, pp. 1761 – 1776, 2011.