A Fuzzy Rule-Based Fingerprint Image Classification

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Abstract
This paper aims to present an improved rule-based fingerprint classification using coherence method and a fuzzy rule-based (or simply fuzzy-based) fingerprint classification. The improved classification using coherence method has been applied to fingerprint images that do not previously produce any singular points while the fuzzy rule-based classification is designed based on the uncertainty in clasifying tented arch, left-loop and right-loop fingerprint images. Two common classification schemes have been used, i.e. 5-class and 4-class schemes. The performance measure uses the success rate and it has been found to achieve 88.38% and 88.33% in the 5-class scheme for the improved rule-based and fuzzy rule-based classifications, respectively. On the 4-class scheme, it has been found to be 92.2% and 92.13%, respectively. The study has also considered weighting the success rate based on the natural proportion of the fingerprints. The success rates have been found to be 89.33% and 90.18% for the improved rule-based and fuzzy rule-based classifications, respectively for the 5-class scheme. On the 4-class, it has been found to be 90.36% and 91.25%, respectively.

Keywords: Fingerprint, classification, rule-based, fuzzy logic

INTRODUCTION
Privacy of one’s identity and information has now become crucial in the digital age. As reported in the 2016 Engineering & Technology magazine, identity has now become a commodity. Theft of one’s identity is growing as information are increasingly circulated online [1]. Security has thus evolved and took on a whole new meaning. It is no longer limited to only feeling safe at home and well provided for. It is now synonymous to taking all sorts of precautions in ensuring only authorized people can have access to information (regardless how trivial it is), especially digital information that can be easily accessed and transmitted. Automatic personal identification plays a vital role today. We can see its applications in mobile cellular phones, banking and finance, e-commerce, and typically in all services that require the use of smartcards or even chips embedded in the human body. And thus we see the rise of biometrics. Fingertips are the oldest biometric signs of identity [2]. Identification through the use of fingerprints has long been used before digital computing and technological advancement in processing and information transfer become so widespread. It is no surprising that when one talks about automatic personal identification, one usually thinks of the fingerprints. The fingerprint ridge and valley patterns on the surface of fingertips formed well-defined orientation features and the ridge endings also provide details referred to as the minutiae. According to Hastings (2006), there are three kinds of features that can be extracted from a fingerprint. Firstly, the large scale patterns of the ridge flow. Secondly, the behavior of the fingerprint ridges, i.e. when they meet or end. Lastly, the detail of the individual ridges, i.e. the location of the sweat pores on the ridges and the irregularities of the ridges [3].

As every individual has ten fingerprints, there are thus millions of fingerprint templates stored in the fingerprint database management system for automatic personal identification. The database would be even larger if it is for the use of forensic investigation. To search and retrieve the fingerprint templates efficiently, images of the fingerprints are normally classified. For example, arch, tented arch, left-loop, right-loop and whorl as depicted in Figure 1. The circle and triangle marks in Figure 1 are the singular points (SPs) of the fingerprints. An SP is a discontinuous point resulted from the sudden changes in the orientation field around the SP. As observed, a core (the circle) is where the OF ridgelines converge while a delta (the triangle) is where the ridgelines diverge. The core and delta points are generally used as markers to categorize fingerprints as belonging to any of the five classes as mentioned. All the classes have at least one core and one delta except the arch class having none. Tented arch, left-loop, and right-loop have a core and a delta each, while commonly a whorl has at least two cores and two deltas as presented in Figure 1.

Based on the review published by Yager and Amin (2004) [4], and Ahmad and Mohamad (2009) [5], fingerprint classification schemes can be divided into a few approaches such as the heuristic, structural, neural and statistical approaches. The most common method of SP detection is by using the Poincare index as proposed by Kawagoe and Tojo (1984) [6]. The disadvantage however is that SPs are often affected by noise. Zhou, Gu and Zhang (2007) and Zhou, Chen and Gu (2009) used an improved Poincare index method by employing a DORIC feature (difference of the orientation values along a circle) to remove spurious SPs [7, 8]. The extraction and representation of the ridge structures of the fingerprints have also been used. The advantage is that since ridge structures can be treated as global features, it can be reliable extracted even in noisy fingerprint images. Chong et al. (1997) used the global geometric shape of fingerprint to calculate the orientation of fingerprint images [9]. Hong and Jain (1999) [10] introduced a rule-based classification that uses SPs and global ridge representation. Although there are various approaches, fingerprint classification can commonly be categorized either as the rule-based or learning-based. The learning-based approach uses half of the image dataset for training/learning and the other half for validation/testing. Examples include the work by Hong et al, which employs the support vector machine and naive Bayes [11], Li, Yau and Wang [12] that uses support vector machine and Liu that uses probabilistic decision tree [13]. On the rule-based approach,
we have seen the work by Hsieh, Shyu and Hung (2009) [14], Liu, Chen and Wan (2008) [15], and Wang and Dai (2007) [16] for instance. Recently, a SP detection algorithm using a quantization approach on the orientation field of the fingerprint image and a rule-based fingerprint classification method have been introduced [17].

In this paper, we have improvised the rule-based classification method as introduced in [17] using a coherence method when no SPs have been detected and also presented a fuzzy rule-based classification due to uncertainty in classifying tented arch, left-loop and right loop. The aim is to see an improvement in the success rate in fingerprint classification. We have presented both methods separately.

Two types of classification schemes have been considered, i.e. 5-class and 4-class. In 5-class scheme, each fingerprint image is classified as belonging to either arch, tented arch, left-loop, right-loop or whorl. In the 4-class scheme, the arch and tented arch are considered only as an arch class. This is due to the relatively low occurrences of both classes in the natural distribution of the fingerprints. The occurrence of the natural proportion of fingerprints according to class has been reported to be 3.7% for arch, 2.9% for tented arch, 31.7% for right-loop, 33.8% for left-loop, and 27.9% for whorl [18].

The performance measure uses the success classification rate (or the accuracy) of classes for comparison. It is given by

\[
\text{Success rate, } SR = \frac{\# \text{ of correctly assigned classes}}{\text{total } \# \text{ of images}}
\]  

The rule-based algorithm according to [17]:

1. If two dominant pairs exist, classify the fingerprint as a Whorl type.
2. If only a single dominant pair exists, do the following:
   i. if absolute angle \(\theta_c\) is between 0° and 45°, calculate \(l\).
   ii. if \(l\) is less than 15pixs or \(\theta_c\) is less 22.5° or \(\theta_d\) is less 10°, classify the fingerprint as a Tented arch type.
   iii. if angle \(\theta_c\) is bigger than 22.5°, classify the fingerprint as a Right-Loop type.
   iv. if angle \(\theta_c\) is smaller than -22.5°, classify the fingerprint as a Left-Loop type.
3. If no dominant pairs exist, classify the fingerprint as an Arch type.

In the algorithm, a dominant pair refers to a pair of linked core and delta belonging to the same ridgeline. From [17], it has been found that the rule-based method has classified less tented arches correctly and assigning it as arches. This is due to the fact that SPs have not been detected in such fingerprint images and thus caused the misclassification as the arch class. To overcome this, the Step 3 of the above algorithm has been improvised as follows:
If no dominant pairs exist, find the center point of the segmented mask. Crop the smoothed orientation field image by a quarter of its original size from the center point. Compute the coherence image. Then, find the connected components for regions where coherence value is less than 0.92. Each connected components must be at least two pixels, otherwise it is considered as noise and deleted. Delete all connected components that are some distance away from the border of the cropped image. If there are two regions left and the distance between the centers of the regions do not exceed a certain limit, classify as a Tented Arch, Right-Loop or Left-Loop as in Step 2 of the algorithm. If there is one region, classify as a Tented Arch. Otherwise, treat the fingerprint as an Arch.

Coherence is a similarity score computed on the smoothed orientation field \( \bar{\theta} \) of the fingerprint image. It compares the similarity of the orientation values of a neighborhood around each pixel. The lower the score, the more the neighborhood is dissimilar (i.e. more discontinuous) to its center pixel. Coherence value at pixel \( (i, j) \) based on Rao (1990) [19] is given by

\[
\text{Coh}(i, j) = \frac{1}{w_C} \sum_{u, v \in \text{w}_C} \cos(\bar{\theta}(u, v) - \bar{\theta}(i, j))
\]

where \( u, v \in \text{w}_C \times \text{w}_C \) defines the points in 2D region of size \( \text{w}_C \times \text{w}_C \) centered at \( (i, j) \).

Fuzzy-Based Classification

Due to a possible uncertainty that might exist in classifying tented arch, left-loop and right-loop for some fingerprint images, a simple three-input one-output Sugeno fuzzy-based decision system has been designed. The system is invoked when a single dominant pair exists. When two dominant pairs or none exists, the algorithm is the same as previously introduced in the improvised method. Hence, the inputs are the orientation angles \( \theta_l \) and \( \theta_r \) and length \( l \) as depicted in Figure 2. In the fuzzy system, the input AngleCore (the \( \theta_c \)) has three membership functions (namely AngleNeg, AnglePos and AngleZero), AngleDelta (the \( \theta_d \)) has one membership function (namely AngleSmall) and Length is described by one membership function (namely LengthSmall). The membership functions are as depicted in Figure 3.

On the other hand, the output is called ClassTRL and is described by three singleton constants representing tented arch (named as Tented with a constant of 0), right loop (named as Right with a constant of 1) and left loop (named as Left with a constant of -1).

The fuzzy inference system uses the default setting in Matlab. Figure 4 shows the rule viewer in Matlab when inputs (AngleCore, Length, AngleDelta) of \( [17^o \ 10\text{pixels} \ 20^o], [27^o \ 25\text{pixels} \ 10^o] \) and \( [-40^o \ 15\text{pixels} \ 10^o] \) are fed into the fuzzy system. The aggregation process can clearly be seen. The observed outputs are 0.131, 0.585 and -0.571, respectively. The final classes will be tented arch, right-loop and left-loop, respectively.

The classification rules as depicted in Figure 3 and Figure 4 are as follows:

1. If AngleCore is AngleZero or AngleDelta is Small or Length is Small then ClassTRL is Tented
2. If Angle is AngleNeg then ClassTRL is Left
3. If Angle is AnglePos then ClassTRL is Right

![Image](p://www.ripublication.com)

**Figure 3:** Input membership functions (a) AngleCore (b) AngleDelta (c) Length

Finally, given the output value of the system, the classification will be

\[
\text{Class} = \begin{cases} 
\text{Tented arch,} & \text{ClassTRL} \leq 0.5 \\
\text{Right loop,} & \text{ClassTRL} > 0.5 \\
\text{Left loop,} & \text{ClassTRL} < -0.5 
\end{cases}
\]

(3)

It must be mentioned that the fuzzy-based classification is merely the improved rule-based classification where Step 2 of the algorithm has been changed to fuzzy system. It is only when single dominant point exists. To show improvement from one approach to another, we have merely shown the results separately by reporting it as two separate classification methods.
RESULTS AND DISCUSSION

All the fingerprints used are from NIST database 4 (NIST-4) [20]. NIST-4 fingerprint database contains 4000 images of size 512x512 taken from 2000 fingers, two images per finger. The NIST-4 has become the most common dataset for evaluating fingerprint classification algorithms [4]. It has also been the most published results on fingerprint classification [13]. The computing environment uses the Matlab on Windows Operating System.

Figure 5 shows the results of coherence method performed on an arch type and a tented arch type fingerprints. The images on the left are the cropped original fingerprint images, the images at the middle are the coherence images while the images on the right are the thresholded (at 0.92) coherence images. It has been thresholded in order to clearly show the connected component. As observed, the tented arch image shows a connected component region.

As more tented arches have been classified correctly in the improved rule-based classification, the overall performance has improved. There are also more loop images being classified correctly. Table 1 and Table 2 show the results of the improved rule-based classification. On the other hand, Table 3 and Table 4 show the results using the fuzzy-based method. The tables of results are tabulated for both 5-class and 4-class schemes.

![Figure 4: Rule viewer for classifying (a) tented arch (b) right-loop (c) left-loop](image)

![Figure 5: Images of coherence method on (a) arch (b) tented arch](image)

<table>
<thead>
<tr>
<th>True Class</th>
<th>Assigned Class</th>
<th>Total</th>
<th>SR</th>
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</tr>
<tr>
<td>R</td>
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<tr>
<td>L</td>
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Table 1: Rule-based success rate for 5-class scheme

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Table 2: Rule-based success rate for 4-class scheme

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</table>

Table 3: Fuzzy rule-based success rate for 5-class scheme
Table 4: Fuzzy rule-based success rate for 4-class scheme

<table>
<thead>
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<tr>
<td>L</td>
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<td>6</td>
</tr>
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Table 5: Comparison of success rates

| | Method | 5-class | 4-class | Total | NSR |
| | | | | | |
| | Rule-based [17] | 85.6% | 92.15% | 87.97% | 90.07% |
| | Improved rule-based | 88.38% | 92.20% | 89.33% | 90.36% |
| | Fuzzy rule-based | 88.33% | 92.13% | 90.18% | 91.25% |

As compared to [17], by using the improved algorithm using coherence method, the success rate (or accuracy) has risen to 88.38% from 85.6% for the 5-class scheme. As for the fuzzy rule-based method, the success rate is 88.33% for the 5-class scheme. This is due to having more tented arches being classified correctly. As for the 4-class scheme, the accuracy has also risen by 0.05% from 92.15% but there is a slight drop of 0.02% for the fuzzy rule-based method.

As the fingerprint images from NIST-4 database are uniformly proportioned (i.e. each class has 800 images), we have also recomputed all the success rates so that it correspond to the natural proportion of the fingerprint classes as reported in [18]. The natural success rate (NSR) results are as tabulated in Table 5. As observed, we can see improvements in the success rates when comparing [17] to the ones introduced in this paper. The fuzzy rule-based method has produced the success rates for both 5-class and 4-class scheme exceeding 90%. Not all the images of NIST-4 are of good quality. Samatelo and Salles (2009) reported that poor quality fingerprint images made up 22.35% of the total images [21]. Hence, with success rates exceeding 90%, the algorithm using fuzzy rule-based method is considered to be working well when compared against the results in [17].

CONCLUSION

A fingerprint classification using fuzzy rule-based method has been introduced. The fuzzy rule-based classification method considers the uncertainty in classifying tented arch, left-loop and right-loop using three features, i.e. two angles and one length. The algorithm also uses a coherence method to overcome the problem when initially no singular points have been detected, and thus increases the chances of detecting the tented arch images. Performance measure using success rates have shown improvements when compared to [17]. Two common classification schemes have been considered, i.e. 5-class and 4-class schemes. The success rates based on the natural proportion of the fingerprints have been found to be 89.33% and 90.18% for the improved rule-based classification using coherence method and fuzzy rule-based classification, respectively for the 5-class scheme. On the 4-class, it is 90.36% and 91.25% respectively.

REFERENCES


