A New Enhancement Of Fingerprint Classification For The Damaged Fingerprint With Adaptive Features

R.Josphineleela[a], M.Ramakrishnan[b] And Gunasekaran[c]

[a]Department of information technology, Panimalar engineering College, Chennai, ilanleela@yahoo.com, Research scholar in Sathyabama University, Chennai, [b] Department Of Information Technology, Velammal Engineering College, Chennai, [c] Department Of Information Technology, Panimalar Engineering College, Chennai

ABSTRACT

In this paper, we propose an new enhancement of the classification for damaged fingerprint database. It is based on the fact that damaged fingerprint image is composed of regular texture regions that can be successfully represents by co-occurrence matrices. So, we first extract the features based on certain characteristics and then we use these features to train a neural network for classifying fingerprints into five classes. The obtained results compared with existing approaches demonstrate the superior performance of our new enhancement.

Keywords

Fingerprint classification, damaged fingerprint,
Texture representation, enhancement, and neural network

1.0 INTRODUCTION

Damaged Fingerprint classification, which classifies fingerprints into a number of predefined categories, is useful as the preliminary step of matching process because it reduces the time taken in fingerprint identification. In this system ,which categorizes a damaged fingerprint into one of the five classes such as whorl(W),right loop(R),Left loop(L),arch(A) ,tented arch(T) by using their global features has been widely used for damaged finger classification. There are many different ways to extract and represent global features which can be largely divided into three main categories: singularity-based approach, structure-based approach and frequency-based approach, In the LOOP pattern are two focal points: the Core or the center of the loop, and the delta. The Delta is the area of the pattern where there is a triangulation or a dividing of the ridges. When recording fingerprints, the delta and the area between the delta and the core must be completely recorded .A Whorl pattern will have two or more deltas. For a whorl pattern, all deltas and the areas between them must be recorded. The Arch pattern has no deltas or core, but it too, must be fully recorded so that its individual characteristics can be readily distinguished

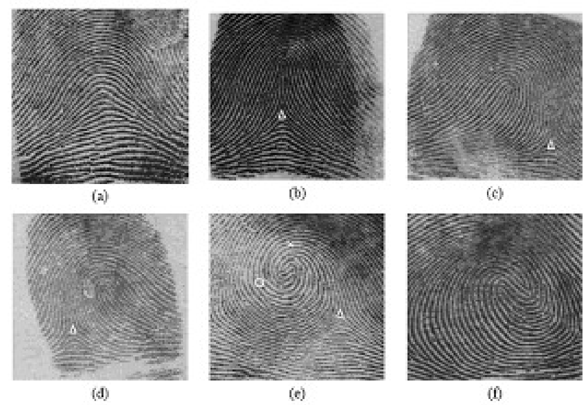

Figure 1: Deformed fingerprints and fingerprint classification schema involving six categories (a) arch (b) tented arch (c) right loop (d) left loop (e) whorl and (f) twin loop. Critical points in a deformed fingerprint called core and delta are marked as squares and triangles. Note that an arch does not have a delta or core one of the two deltas in (e) and both the deltas in (f) are not imaged. A sample minutiae ridge ending and ridge bifurcation(x)is illustrated in(e)Each image is 512*512 with 256 gray levels and is scanned at 512 dp resolution. All features points were manually extracted by one of the authors.

2.0 PREVIOUS WORK

Many approaches to automatic fingerprint classification have been presented in the literature and the research on this topic is still very active. The approaches are mostly based on two main features in a damaged finger.1) Global ridge and furrow structures that form special patterns in the central region of the damaged finge.2) Local ridge and furrow minute details. A damaged finger is classified based on the second type of features.

There are two main approaches for extracting information about fingerprint ridge structures. One method is based on developing a mathematical model of fingerprint ridges and representing the fingerprint using these models. Another approach uses record characteristics of the ridges and stores this information for classification.

Recently, some papers have reported very good results in the automatic classification of fingerprint databases.

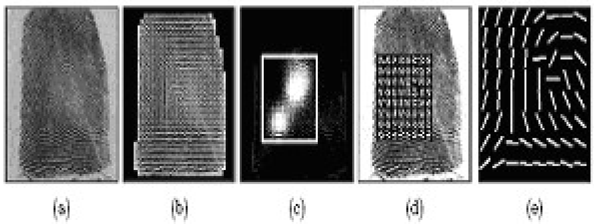

Figure 2: The sequence images of adaptive feature extraction (a) original image (b) orientation field(c) variation field (d) feature region (e) directional value of the feature region

Jain used the Gabor filter in four directions to extract features form fingerprints for classification .In another attempt; they have stored the shape information about the structure of fingerprint ridges for their classification scheme. Each ridge is classified as nonrecurring, recurring, or fully recurring. They obtained a 94.8% correct classification. Jain and L.Hang have proposed a mathematical model for each fingerprint class that represents the ridge structure of fingerprints belonging to that class. They obtained an 91.3% correct classification .chang and Fan have developed an alternate fingerprint representations that captures structural information. Yaoetal have developed an algorithm based on support vector machines. They obtained a 94.7% correct classification.

We propose enhancement method for the damaged finger classification based on the fact that fingerprint image is composed of regular texture regions that can be successfully represents by co-occurrence matrices. We first apply histogram equalization for reducing the influence of the noise in damaged fingerprint images. Then, a series of simple morphological operations will be applied to emphasize the ridge structure of damaged fingerprint patterns.The texture context of fingerprint structure will be represented by co-occurrence matrices that specify the relation of neighbor pixels in certain distance in a given direction. Based on the applied co-occurrence matrices, some features are defined and extracted. Finally, based on neural network the system will be trained and used for classify the damaged fingerprint databases on four major classes.

3.0 HISTOGRAM EQUALIZATION

Because there are many noises in original fingerprint image, an image enhancement algorithm such as histogram equalization is usually applied to reduce the influence of the noise in fingerprint image and to emphasize the ridges structures of damaged fingerprint patterns.

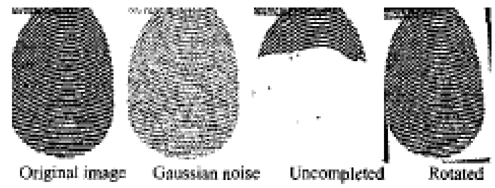

Figure4: damaged fingerprint classification experiment samples

4.0 NORMALIZATION

This part of algorithm has significant effect on total performance of algorithm. The problem is that the total number of compared pixels pairs is different due to the angular relationships. Moreover, the size of images in the databases is not the same. To overcome these problems, it is necessary to normalize the co-occurrence matrices. We used the normalized correlation algorithm proposed by kim et al to normalize all co-occurrence matrices.

5.0 FEATURE EXTRACTION

In the feature extraction phase, the feature region is divided into 8*8 blocks (fig 2 (d)) and their directional values are estimated [fig 2(e)].here the directional field θ is calculated similarly to the orientation field computation except the size of each block that is different for each fingerprint due to the adaptively selected feature region. The proposed method extracts the 256 dimensional feature by estimating the difference between the directional value θ(i,j) of the (i,j) the feature-block and each of four directions,0o,45o,90o and 135o as follows

$$f_k = \begin{cases} -\partial_{i,j} \text{ if } \partial_{i,j} < 0 \\ \pi - \partial_{i,j} \geq \frac{\pi}{2} \end{cases} \qquad (1)$$

$$\partial_{i,j} \text{ Otherwise}$$

Where $\partial_{i,j} = \theta(i,j) - \gamma,\ \gamma = \{0, \pi/4, \pi/2, 3\pi/4\}$ (2)

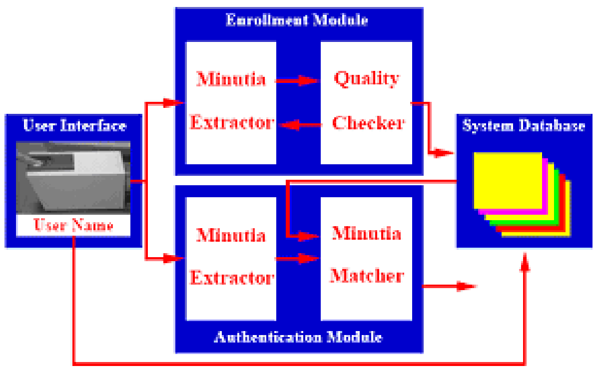

Figure 3: Architecture of an automatic identity authentication system

6.0 CLASSIFIER

For the classification task, an artificial feed-forward neural network with two hidden layers is used. This neural network has

Table 1: *Five classification results on the NIST-4 database*

True Class	Assigned class				
	A	T	L	R	W
A	88	13	10	11	0
T	17	384	54	10 10	5
L	31	27	75	3	25
R	30	47	3	70	15
W	6	1	25	10	75

A-Arch-Tented Arch-Left Loop-Right Loop-Whorl

60 input neurons (12 features multiplied by 5 co occurrence matrices) and 5 output neurons corresponding to 5 classes of arch, whorl, right loop, left loop, and tented arch. The number of neurons in hidden layers is determined experimentally.

The classification algorithm summarized here (see Figure ii) essentially devices a sequence of tests for determining the class of a fingerprint and conducts simpler tests earlier in the decision tree. For instance, two core points are typically detected for a whorl (see figure 11) which is an easier condition to verify than detecting the number of type-2 recurring ridges. Another highlight of the algorithm is that if does not detect the salient characteristics of any category from features detected in a fingerprint, it recomputed the features with a different pre processing method. For instance, in the current implementation, the differential pre-processing consists of different method/scale of smoothing. As can be observed from the flowchart that algorithm detects (i) whorls based

upon detection of either two core points or a sufficient number of type-2 recurring ridges; (ii)arch based upon the inability to detect either delta or core points; (iii)left(right)loops based on the characteristics tilt of the symmetric axis, detection of core point and detection of either a delta point or sufficient number of type-1 recurring curves; and(iv) tented arch based on relatively upright symmetric axis, detection of core point and detection a delta point or sufficient number of Type-1 recurring curves

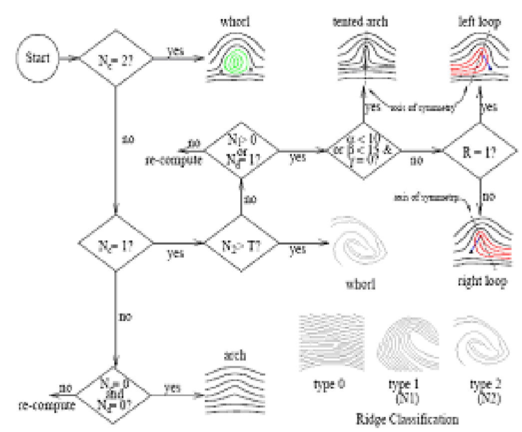

Figure 5: Flowchart of damaged fingerprint classification .The re-compute involves starting the classification algorithm wit different preprocessing (e.g. smoothing of the image)

Table 1shows the results of the fingerprint classification algorithm on the NIST-4 database which contains 4,000 images (image size is 512*480) taken from 2000 different fingers,2 images per finger. Five fingerprint classes are defined:1)Arch ,ii)Tented arch, (iii)left loop,(iv)Right Loop and (v) Whorl .Fingerprints in this database are uniformly distributed among these five classes (800 per class).The five class error rate in classifying theses 4,000 fingerprints is 12.5% the confusion matrix is given table 1;numbers shown in bold font are correct classifications for damaged fingerprint. Since a number of fingerprints in the NIST-4 database are labeled as belonging to possibly two difference classes, each row of the confusion matrix in Table 1 does not sum up to 800.For the five class problem, most of the classification errors are due to misclassifying a tented arch as an arch. By combining these two arch categories into single class, the error ratedropsfrom12.5% to 7.7% besides the tented arch-arch errors, the other errors mainly come from misclassifications between arch/tented arch and loops and due to poor image quality

7.0 EXPERIMENTS

To test proposed system, two databases were used. The famous databases are containing FVC2000, FVC2002, and FVC2004 from biometric system Laboratory University of Bologna and other from Neurotechnologija web site nameVeriFinger_sample_DB.NIST4 fingerprint database, which consists of 4000 images (2,000 fingerprint pairs) for our experiments, the first 1,000 pairs of fingerprints (F0001 to F1000 and S0001 to s1000) were used for training and the reaming 1,000 pairs (F1001 to F2000 and S1001 to S2000) were used for testing.

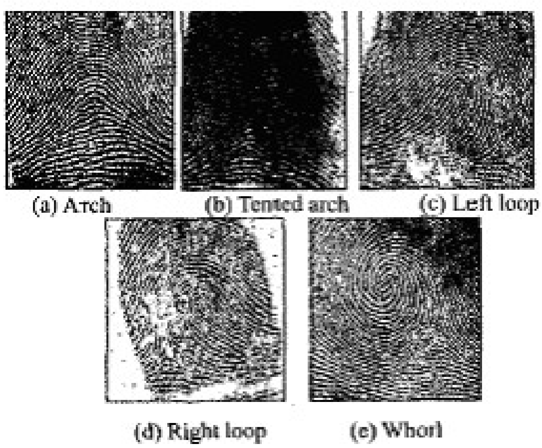

Figure 6: Five classes of damaged fingerprint

A. Adaptive features versus non adaptive features

Two types of fingerprint features were used for comparison experiments: adaptive and non adaptive. The adaptive features were extracted by using the proposed algorithm, while the non adaptive features were obtained by applying feature regions of fixed size (128*128,192*192,256*256 and 320 *320 pixels)

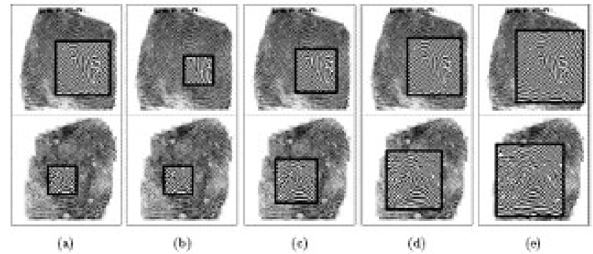

Figure 7: Examples of the selected feature region for two(upper and lower)different fingerprints(a)Results of the adaptive approach, and others are results of the non adaptive approaches where the sizes of feature regions are fixed as:(b)128*128,(c)192*192,(d)256*256 and (e)320*320 pixels.

8.0 CONCLUSION

We have proposed a new enhancement of fingerprint classification based on the structure approach to damaged fingerprint .The features extracted from the matrices can well characterize the regular texture of damaged fingerprint images. We obtained the results 94.8%.

REFERENCES

1. R. Cappelli, A. Lumini, D. Maio and D. Maltoni, Fingerprint classification by directional image partitioning, *IEEE T. Patt. Anal.* **21** (1999) 402–421.

2. J.-H. Chang and K.-C. Fan, A new model for fingerprint classification by ridge distribution sequences, *Patt. Recogn.* **35** (2002) 1209–1223.

3. J.-H. Hong, J.-K. Min, U.-K. Cho and S.-B. Cho, Fingerprint classification using one27vs-all support vector machines dynamically ordered with naıve Bayes classifiers, *Patt.Recogn.* **41** (2008) 662–671.

4. A. K. Jain and R. C. Dubes, *Algorithms for Clustering Data* (Prentice Hall, 1988).

5. A. Jain, L. Hong and R. Bolle, On-line fingerprint verification, *IEEE T. Patt. Anal.* 31 **19** (1997) 302–314.

6. A. K. Jain, S. Prabhakar and L. Hong, A multichannel approach to fingerprint classification, *IEEE T. Patt. Anal.* **21** (1999) 348–359.

7. K. Karu and A. K. Jain, Fingerprint classification, *Patt. Recogn.* **29** (1996) 389–404.

8. M. Kawagoe and A. Tojo, Fingerprint pattern classification, *Patt. Recogn.* **17** (1984)295–303.

9. L. I. Kuncheva, Using measures of similarity and inclusion for multiple classifier fusion by decision templates, *Fuzzy Set. Syst.* **122** (2001) 401–407.

10. L. I. Kuncheva, Combining Pattern Classifiers: Methods and Algorithms (Wiley-Interscience, 2004).

11. L. I. Kuncheva, J. C. Bezdek and R. P. W. Duin, Decision 1 templates for multiple classifier fusion: An experimental comparison, *Patt. Recogn.* **34** (2001) 299–314.

12. J. Li, W.-Y. Yau and H. Wang, Combining singular points and orientation image information for fingerprint classification, *Patt. Recogn.* **41** (2008) 353–366.

13. R. M. Rifkin and A. Klautau, In defence of one-vs-all classification, *J. Mach. Learn.Res.* **5** (2004) 101–141.

14. C. I. Watson and C. K. Wilson, *Fingerprint Database. National Institute of Standards and Technology*, Special Database 4, FPDB, 1992.

15. L. Wang and M. Dai, Application of a new type of singular points in fingerprint classification, *Patt. Recogn. Lett.* **28** (2007) 1640–1650.

16. N. Yager and A. Amin, Fingerprint classification: A review, *Patt. Anal. Appl.* **7** (2004)77– 93.

17. Y. Yao, G. L. Marcialis, M. Pontil, P. Frasconi and F. Roli, Combining flat and structured representations for fingerprint classification with recursive neural networks and support vector machines, *Patt. Recogn.* **36** (2003) 397–406.

18. Q. Zhang and H. Yan, Fingerprint classification based on extraction and analysis of singularities and pseudo ridges, *Patt. Recogn.* **37** (2004) 2233–2243.