A NEW HUMAN FINGERPRINT IDENTIFICATION APPROACH

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ABSTRACT: The paper presents a fingerprint classification system and its performance in an identification system. The classification scheme is based on fingerprint feature extraction, which involves encoding the singular points (Core and Delta) together with their relative positions and directions obtained from a binaries fingerprint image. Image analysis is carried in four stages, namely, segmentation, directional image estimation, singular-point extraction and feature encoding. A fuzzy-neural network classifier is used to implement the classification of input feature codes according to the well-known Henry system. Fingerprint images from NIST-4database were tested and, *98.5%* classification accuracy was obtained for the five classes- problem.

Keywords: Human, Fingerprint, Fuzzy – neural, NIST - 4

1. INTRODUCTION

Fingerprint identification and verification are oneof the most significant and reliable identification methods. It isvirtually impossible thattwo people have the samefingerprint, (Probability1 in 1.9E15) [l]. Io fingerprint identification and verification applications world-wide, alarge volume of fingerprints are collected and stored for a wide range of applications, including forensics, civilian,commercial and law-enforcement applications. Automatic identificationof humans based on fingerprints requires theinput fingerprint to be matched with a large number offingerprints in a database (for example, theFBI databasecontains approximately70 million fingerprints). To reduce the search time and computational complexity, it is desirableto classify the database into accurate and consistent classesso that input fingerprint is matched only with a subset of thefingerprints in the database. The nature of each applicationwill determine the degree of accuracy required. For example, a criminal investigation case may require higher degree match than access control case system. Many automatic fingerprint classification methods, such as method introduce in [3],[5] and [9]-[12], rely on point patterns in fingerprints, which form ride endings and bifurcation unique to each person. Traditionally, activities to solve a pattern recognition task are twofold. First, a set of features has to be found describing the object(s) being classified. Second, after a set of features has been found, a classification mechanism is chosen and optimized. These two steps are highly interdependent, since the choice of features influences the conditions under which a classifier operates, and vice versa. With the advent of neural networks however,more and more problem are solved by simply feeding largeamounts of ‘drawdata’ (e.g. images, sound signals, stock market index ranges) to a neural network. This approach,however,is not feasible in fingerprint classifications, which are highly susceptibleto noise and elastic distortions. Therefore, it is desirable to extract features from the imagesthat are invariant to such distortions. During training the classification networklearns the association and significance of features.An attempt has been made previously to studyfuzzy logic and artificial neural network techniques infingerprint identification[2]. It was shown that a trade-offexists between the trainability of simple networks and itsunderstandability: the larger the network, the easier to train and the most reliable training results can obtain. The conclusion was that fuzzy-neural networks could be usefulas adaptive filters in fingerprint classification tasks, but thatgreat care has to be taken in choosing the networkarchitecture and training algorithm. Inthis paper an implementation of a fuzzy-neural network for fingerprintclassification system is presented. The rest of this paper is organized as follows.In section 2the proposed featureextraction algorithmis reported. Section 3presents a brief discussion of fingerprint classification using a fuzzy-neuralnetwork(FNN) learning approach. Section 4 presents the resultsof FNN classification after training and testing. Finallysection5 draws some conclusions from the study.

2. FINGERPRINT FEATURE EXTRACTION (FFE)

The central problem in designing a fingerprint classification system is to determine what features, should be used and howcategories are defined based on these features. There are, mainly two types of features that are useful for fingerprint recognition system: (i) local ridge and valley details(minutiae) which have different characteristics for different fingerprints, and (ii) global pattern configurations, whichform special patterns of ridges and valleys in the central region of the fingerprint. The firsttype of features carries forthe information about the individuality of fingerprints and the secondtype of features carry information about thefingerprint class. Therefore, for fingerprint classification, the features derived from the global pattern configurations shouldbe used. These features should be invariant to the translationand rotationof the input fingerprint images. Generally, global fingerprint features can be derived from the orientation fieldand the global ridge shape.The orientation field of a fingerprint consists of the ridgeorientation tendency in local neighbourhoods and forms an abstraction of the local ridge structures. It has been shownthat the orientation field is highly structured and can beroughly approximate by the core and delta models[13],which are known as singular points details. Therefore,singular points details (see Figure3)and their relationshipscan be used to derive fingerprint categories. On other hand,global ridge shape and directional field also providesimportant clues about the global pattern configuration of thefingerprint image.Many different algorithms for singular points extraction areknown from the literature. Examples of these algorithmsare**,** sliding neural networks [3], local energy of directional imageprocessing[4], ratio of the sine of the fingerprint image intwo adjacent regions[1], and singular point indexing [5].However, these algorithms give somewhat unsatisfactoryresults; in particular the rate of accuracy is very low in most cases. Post-processing steps are necessary to interpret the outputsof the algorithms and to makethe final decisions,resulting in missed and false singular points. In this paper, weshow that a singular points verification stage based on re-examining the grayscale profile in a detected singular-points spatial neighbourhoodof the image can improve theclassification performance. Additionally, we show that afeature encoding stage which relies on the images estimated directional field can improve the classification performance.

A. Segmentation of Fingerprint Image

Segmentation of an image is used to pre-processappropriately; in order to remove noise froman image sample and itisoften a key step in interpreting the image. Imagesegmentation is a process in which regions or features sharingsimilar characteristics are identified and grouped together. Image segmentation may use statistical classification,thresholding, edge detection, region detection,or anycombinationof these techniques [9, 11, 12]. The output of thesegmentation step is usually a setofclassified elements, suchas regions or boundaries. Thresholding is the simplest way to perform segmentation, and itis used extensively in many image-processing applications. It is based on the notion that regions corresponding to different objecttypes can beclassified by using a range function applied to the intensityvalues of image pixels. The assumption is that different objecttypes will have distinct frequency distributions and can be discriminated on the basis of the mean and standard deviationof each distribution. Thus, given a two-dimensional image$I(x, y)$, we can define a simple threshold rule to classifydifferent object types. Thresholdof gray-level images to black and white is based ona two-stage process: GeneralThreshold (GT) of the whole image in the first stage andRegional Average Thresholding (RAT)in the second stage. A hypothetical frequency distribution$f(I)$of intensity values isused such that, low intensity values correspond to black whilehigh intensity values correspond to white.

- ***General Thresholding*** (GT)

In the GT scheme, the process of binarising ofthe graylevel image to a black and white image is carried out bylooking at each pixel on the fingerprint image and decidingwhether it should be converted into black(0) or white (255), i.e. converted to 0 and 1 values. The decision is made bycomparing each numeric pixel of gray-level image with afixed number called a threshold level to make the decision. Ifthe pixel is less than the threshold level, the pixel value is setto zero; otherwise it is set to255. The thresholding scheme can be expressed as follows in equation(1).

$$P(i,j) = \begin{cases} 255 \ \ if \ I(i,j) < T \\ \quad 0 \ \ if \ I(i,j) \leq T \end{cases} \tag{1}$$

Where $I(i,j)$indicate the original image, $P(i,j)$indicates theoutput binary image, T is the threshold level, and$(i = 0, \dots \dots .. N, j = 0 \dots \dots \dots M)$ $r$epresent the image size.

- ***Regional Average Thresholding***

Applying GT to an image may cause some feature lose?This is because; the average gray level is not, usually, thesame in different parts of the original image (e.g. background and foreground). This is particularly the case in fingerprintimages, which are directly effected by different kinds of theskin affectionsor noise. Regional Average Thresholding (RAT) is a threshold scheme for fingerprint images, whichhas been proposed to overcome the problem of the GT. Thus,the original image may be partitioned intosmall regions, suchas, *32X32*or *16X16* pixel windows. Thresholding is then carried out within each region, using the gray-level average ofeach window. The average Grey levels is calculated as shown in equation(2).

$$T = 1/N^2 \sum_{i=0}^{N} \sum_{j=0}^{N} I(i,j) \tag{2}$$

In this paper a *16X16* pixel window scans the imagestarting from the left most comer of the image.An averagethreshold level is calculated within each window and moved to next window. The process continues until the bottom rightcomer of the image. Since the average thresholdlevels arecalculated regionally, more features are preserved in comparison withGT. This stage also eliminates the fields that contain no information, such as, the edgesof the fingerprint images.In order to extract singular point we have proposed to calculate the directional field of an image. The directional field describes the local orientations of the ridge and valley structures in a fingerprint. In this paper, the directional field of a fingerprint image is computed in four sub-directions, as shown in Figure 2. Firstly, the image is partitioned into small blocks (we chose *5X5* blocks). Numeric gradients are computed for each sub-direction from the pixel intensities (equation 3). The dominant direction is then given by the sub-direction with the smallest numerical value. By sliding the *5X5* mask in Figure 2 over the threshold image P, we calculate the minimum sum of differences (sod) for the central pixel, c

(Figure 2). Each block is then represented by the gradient value of the dominant sub-direction:

$$V(c,c) = min_d(\sum|P(c,c) - P(i,j)|) \quad (3)$$

where, $P(i,j)$ are binary values, in a given direction, d.

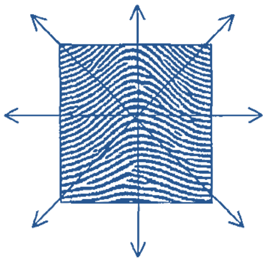

Fig.1: Direction computation in 4 main directions

4		3		2
1		c		1
2		3		4

Fig. 2: A *5X5* direction mask with its geometric orientations

The directional field of an image, V creates a $M/q \times N/q$ reduced-size image, which decreases the dimensionality ofthe input features and hence the complexity of the featureextraction algorithm. The logic behind the working of the directional field method is that a peak in the histogram of adirectional image in a region indicates that there exists a clearridge, because a ridgeline results in points of the same direction in the region. That is, if a clear ridge exists in a region, it expressly means itis foreground, which gives rise to a peak in the histogram. The limitation of this method is thatin perfect uniform region $P(c,c) = P(i_m, j_m)$**,** for m varying in any direction, thus equation(3) become undefined. However,the directional criterionis very good for low contrast and noisy images, besides giving good resultsfor modest quality(clarity in ridges) of fingerprint images.

B. Singular Points Extraction

Singular points, namely the Delta and the Core, are manifest as discontinuities in the directional image.They areclearly visible in the fingerprint image in Figure3. Deltapoint lies on a ridge ator in front of and nearest to the centerof the divergence of the type lines.A Core point is theapproximate centerof the finger impression. Using thereduced-size directional image, we determine the candidatesingular points, including their relative orientations anddirections in the fingerprint image as follows:

A pixel, c (Figure 2) is a Delta point if:

$$16 \leq \sum_c P(x,y) \leq 20 \qquad (4)$$

A pixel, c (Figure2) is a Core point if:

$$\sum_c P(x,y) \geq 21 \qquad (5)$$

Otherwise, the point, c is undefined; where the pixelintensities$P(x,y)$are summed around the pixel, c.

Fig. 3: Singular points on fingerprint

C. Feature Encoder

A feature encoder is applied for representing the vectorof features extracted from fingerprints. This is a list ofsingular pointswith accompanying attribute values. Theinformation we are interested includes:

1. Number of deltas, ***DeltaNo;***
2. Number of cores, ***CoreNo;***
3. Global directional field orientation, ***ImageDir***I.
4. Core direction, ***CoreDir;***
5. Relative Core-Delta position ***DeltaPos.***

TABLE 1: TYPICAL FEATURES FOR DIFFERENT CLASSES

Type	**Delta No.**	**Core No.**	**Image Dir**	**Core Dir**	**Delta Pos**
A	0	0	1	0	0
T	1	1	3	3	1
W	2	2	3	2	4
R	1	1	4	4	2
L	1	1	2	2	3

Table-1 shows an example of typical feature vectors fordifferent fingerprint classes, namely, Arch, Tended arch, Whorl, Right-loop, Left-loop (see Figure5). Due to noiseand errors in segmentation and feature extraction algorithms, it is generally the case that the actual feature vectors deviate.Significantly from the canonical case. For this reason classifiers that can cope with such deviations are desirable. Inthis paper, it has been proposed to use a Fuzzy-neural. classifier.

3. FINGERPRINT CLASSIFICATION USING FUZZY-NEURAL. CLASSIFIER

Fuzzy-neural hybrid systems combine the advantages of fuzzy systems, which deal with explicit knowledge that can beexplained and understood, and neural networks, which deal with implicit knowledge that can he acquired by learning[6]- [8].In the fuzzy-neural network, the neural network part isprimarily used for learning and classification and retrieval.The neural network part automatically generatesfuzzy logicrules and membership functions during the training period.In addition even after training, the neural networks keepsupdating the membership functions andfuzzy logic rules as it learns more and more from its input signals. Fuzzy logic, on
the other hand,is used to infer and provide a crisp ordefuzzified output where ambiguities existin the input fuzzy parameters. In order to train the classifier, two data sets of feature codes were prepared. The first data set is used fortraining the network and the second for testing. Fuzzificationof the operation of the classifier by generating membershipfunctions around the typical values of feature codes, easily explained with linguistic terms.

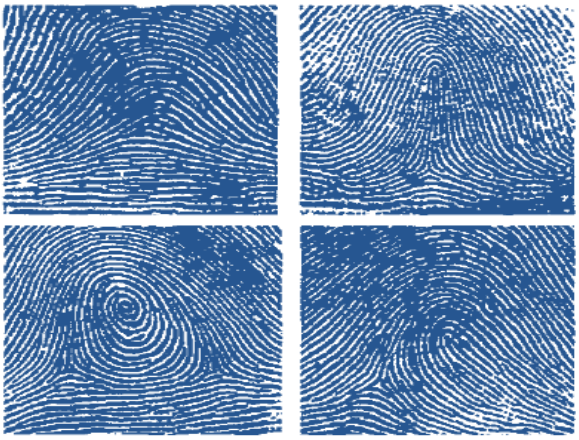

Fig. 4: Fingerprint classes -tap left - Arch; top right Tended arch;
bottom left - Whorl; bottom Right-loop

As an example we know thatthe CoreNo varies from0 to 2. We could therefore form "fuzzy" CoreNo as none (O..l), small (l..2), and large (>= 2). The overall network was constructed through an automaticnetwork construction process, a feature of NeuFrame^{TM}software[14]. Typical rules from the network are illustrated below:

1. IF DeltaNo issmall AND CoreNo is small AND ImageDir issmall AND CoreDir is**small** AND DeltaPos is right THEN Lis equal(0.91) OR L is equal (0.09)
2. IF DeltaNo is medium AND CoreNo is **small** ANDImageDir issmall AND CoreDir is AND DeltaPos is rightTHEN L is equal(0.91) OR L is equal (0.09)
3. IF DeltaNo is **small** AND CoreNo is medium AND ImageDir is**small** AND CoreDir is small AND DeltaPos isright THEN L is equal(0.91) OR L is equal (0.09).
4. IF DeltaNo is medium AND CoreNo is medium AND ImageDir is**small** AND CoreDir is small AND DeltaPos is right THEN L is equal (0.91) OR L is equal (0.09).

4. Experimental Results

Results of the performance of the classifier were obtained by querying the fuzzy-neural classifier using the test set, and comparing known class labels against the classifier outputs. The classifier outputs. The classifier was trained and tested on 4000 images in the NIST-4 database for the five-class problem. We note, therefore, that the overall network consists of five networks, each corresponding to the output classes, A,T,W,R,L. The results, presented in Table-II, were obtained after passing feature encoded vectors of the FFE algorithm. The result shows that the classification accuracy varies widely across the different classes. Initial investigations have indicated that this may be due to the generalization characteristic of neural networks, which causes mis-classification among fingerprints with similar features. It is suggested that this can beovercome using a different feature extraction scheme. Alternatively, the occurrence of mis-classification can be studied further and the confusion probabilities used in resolving the final output classes.

TABLE-II EXPEREMENTAL RESULTS FROM ANC

Class Type	Accuracy
A	85.4
T	95
W	98.2
R	96.4
Lz	84.0

5. CONCLUSIONS

The aim ofthis paper has been' to present an implementation of a fingerprint classification problem usingfuzzy-neural networks. Fingerprint classification provides an important mechanismfor automatic fingerprint recognitionsystems.We have proposed a simple and flexible fingerprint classification algorithm, which classifies input fingerprintsinto five categories according to the number of the core and delta (singular points), and their relative (x, y)positions in animage. The classifier was tested on4,000 images in the NIST- 4 database. For the five-class problem, classification accuracy as high of 98.5% is achievable. By incorporating a rejectoption, the classification accuracy can be increased further. The feature extraction algorithm demonstrates how,fromdirectional fields of an image, accurate detection of thesingular points and the orientations ofthose points can be obtained. While it is true that this method was not tested forall possible features of fingerprints, it has been shown to beeffectively in identifying singular-point in all cases tested.

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