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REVIEW OF FINGERPRINT CLASSIFICATION METHODS BASED ON ALGORITHMIC FLOW

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Abstract- Fingerprints are the oldest and most widely used form of biometric identification. The fingerprint classification task consists of associating a given fingerprint to one of the existing classes already recognized in the literature. Automatic fingerprint identification system (AFIS) needs to access a large volume of data stored in the database for fingerprint identification. A search over all the records in the database takes a very long time, so the goal is to reduce the size of the search space by choosing an appropriate subset of database for search. Classifying a fingerprint images is a very difficult pattern recognition problem, due to the small interclass variability, the large intraclass variability. In this paper, we have proposed a sequence flow diagram which will improve the clarity on designing algorithm for fingerprint classification based on various features extracted from the fingerprint image. This paper also discusses in brief the ways in which the features are extracted from the image. Existing fingerprint classification methods are categorized the based on the features used as input for classification.
Key words - Singular points, Ridge flow, Orientation map, Neural Network, Multiple classifier.

INTRODUCTION

The identification of a person requires a comparison of her fingerprint with all the fingerprints in a database. This database may be very large (e.g., several million fingerprints) in many forensic and civilian applications. In such cases, the identification typically has an unacceptably long response time. The identification process can be speeded up by reducing the number of comparisons that are required to be performed. A common strategy to achieve this is to divide the fingerprint database into a number of bins. A fingerprint to be identified is then required to be compared only to the fingerprints in a single bin of the database based on its class. The well-known Henry's Classification scheme divides a fingerprint structure into three major classes or patterns namely Arch, Loop and Whorl. These classes are further divided by researchers into arch, tented arch, left loop, right loop and whorl.

As shown in Figure. 1 displays an algorithmic flow for selection of features and classification of fingerprint. Beginning with generation of orientation map or ridge flow, it follows the flow to be used for different methods for classification. Orientation map helps to locate singular points. Hybrid class is formed by the combination of the orientation map, ridge flow or singular points. Features are extracted by using the above techniques followed by classification of fingerprint. These features can be given as input to neural network, clustering algorithm, hidden markov model, rule based approach, genetic algorithm, etc to improve the performance of classification.

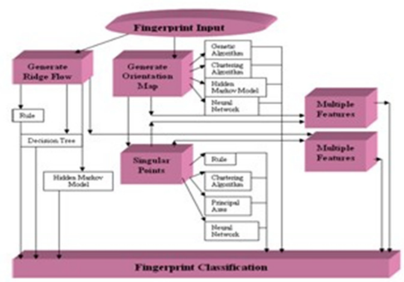

Fig.1-Algorithmic approach for fingerprint classification

RELATED WORK

This section glances through various fingerprint classification methods based on the feature extracted. The following features are used for differentiating between various methods: Orientation map, Core and Delta points, Ridgeline flow, Transform based features and Multiple Classifiers based methods.

Orientation map

Orientation map describes the orientation of the ridge-valley structures. The Direction Field can be derived from the gradients by performing some averaging operation on the gradients, involving pixels in some neighborhood [23]. Wei and Chen [14] have suggested an improvement in the computation of direction field, which gives more accurate information about the ridges and the valleys.

Cappelli, Lumini, [8] have presented a new approach for fingerprint classification which uses masks for partitioning orientation image. Dynamic masks help to bring stability during partition process. Sylvain et al. [9] uses orientation field to capture features which is given to Self Organizing Map for further classification. Guo and He [10] have presented a statistical approach for fingerprint classification using Hidden Markov Model (HMM). HMM is like a finite state machine in which not only transitions are probabilistic but also output. Feature vector is obtained by calculating orientation field and then getting the local orientation for each block. This observation vector is fed as input to HMM. Krasnjak and Krivec [11] have used quad tree principle to divide the direction map according to homogeneity,which is used as feature vector for neural network using MultiLayer perceptron.Xuejun and Lin [12] have proposed an algorithm based on genetic programming for fingerprint classification. In this paper genetic programming tries to explore a huge search space which cannot be done by human experts.

Features are generated from orientation field using genetic programming. Jiang, Liu and Kot [13] have given a combined classification approach by performing exclusive and then continuous classification [26]. In exclusive classification, first clustering is performed to form similar groups of data in the database then the query image's orientation field is compared with the cluster representative which reduces search time. In continuous classification the query images orientation map is compared to the fingerprints in the received cluster. Luping Ji, Zhang Yi [15] have presented classification approach using Support Vector Machine (SVM). SVM is a learning theory useful in pattern classification. Four directions (0, π/4, π/2, 3π/4) are used for orientation field representation. Fingerprints are then classified using the output of the trained classifier. Sivanandam and Anburajan [16] have used neural network for classification. Jiaojiao Hu, Mei Xie [18] have introduced a classification technique using combination of genetic algorithm and neural network. Orientation field is given as input to genetic programming process. After the process is over, backpropagation network and Support Vector Machine (SVM) are used for classification of fingerprints.

Core and Delta points

Within the pattern areas of loops and whorls are enclosed the focal points which are used to classify fingerprints. These points are called as core and delta. The delta is that point on a ridge at or in front of and nearest the center of the divergence of the type lines. The core is present when there is atleast one ridge that enters from one side and then curves back, leaving the fingerprint on the same side. Accuracy in finding singular points is reduced if the image is of poor quality [28]. Approaches for singularity detection operate on the fingerprint orientation image. Poincare index proposed by Kawagoe and Tojo (1984) is an elegant and practical method to detect singular points. It is computed by algebraically summing the orientation differences between adjacent elements [22]. Poincare index is evaluated for every pixel in the directional image. M.Usman, Assia Khanam [19] have suggested an optimal way of locating core point by extracting the region of interest. Wang and Zhang [1] have enhanced the fingerprint image to reduce the effect of noise and detected singular points using Poincare Index. Feature Vector is obtained by finding the region of interest [24] using core point. Finally clustering algorithm is used for classification.Liu and Zhang [2],Klimanee and Nguyen [3] and Msizia and Ntsika [5] have preprocessed image and have presented a novel way of locating core and delta points. Classification is done by defining rules based on the number of singular points.Classification is performed using principal axes in [3]. Srinivasan and Rakesh [4] have proposed a technique based on neural network. They have used PCA (Principal Component Analysis) to reduce the size of the feature space. Singular points detected are then given to SOM (self-organized map) which is an unsupervised learning neural network.

Ridgeline Flow

The flow of the ridges is an important discriminating characteristic. It is not always easy to be reliably extracted from noisy fingerprints. It is a feature more robust than singular points. The ridge line flow is usually represented as a set of curves running parallel to the ridge lines; these curves do not necessarily coincide with the fingerprint ridges and valleys, but they exhibit the same local orientation.Andrew [6] has described a classification technique based on the characteristics of the ridges. Two new classifiers have been presented in the paper. The first classification described is by using Hidden Markov Model (HMM). In fingerprint image the direction changes slowly hence HMM is suitable here for classification. The ridgelines are typically extracted directly from the directional image, then the image is binarized and thinning operation is performed, features are extracted that denotes the ridge behavior. The second classification described is using Decision Trees. Features are extracted and classified using a decision tree approach. Features are extracted at significant points on the ridges and a decision tree is constructed based on the questions about the features and the relationship between those features. Neeta and Dinesh [7] have presented an approach for classification based on ridge flow. To reduce computation high ridge curvature region is extracted using Sobel operator and direction map. HRC is calculated based on the values of the slope within the block. After locating HRC, Ridge tracing is performed. Hye-Wuk and Lee [17] have published classification approach using HMM. Features are extracted from orientation field by locating the direction of the extracted ridge which is then taken as input for HMM for designing fingerprint models.

Transform based

Fast Fourier Transform computes the Discrete Fourier Transform (DFT) and produces exactly the same result as evaluating the DFT definition directly; the only difference is that an FFT is much faster. Karungaru and Akamatsu [20] have extracted features for classification using Fast Fourier Transform. For complex computation FFT gives a significant speed. Neural Network is used for classification using Backpropagation Algorithm as its learning method.

Multiple Classifier

Different classifiers potentially offer complementary information about the patterns to be classified, which may be exploited to improve performance.Jain, Prabhakar, Hong [21] have come up with a novel scheme to represent ridges and valleys of a fingerprint. It uses orientation field to detect core and delta points. 2 stage classification is done, firstly K nearest neighbor to find most likely classes and secondly neural network for further classification.Zhang,Yan [25] have used core and delta points and ridge flow as feature vector. Using singular point, ridge is traced in opposite directions to find the turn number. It then uses rules for classification. Wang,Chen [14] is based on singular points and orientation map. Their feature vector includes number of singular points, angle from delta to core, average of the directions in region of interest. Further, Fuzzy Wavelet Neural Network is used for classification.Wei and Hao [27] have used singular points and ridge flow mthods for feature extraction. In the first level ridgelines are classified and classification is done based on it. In the second level the ridge count between singular points is used for further classification.

SUMMARY AND CONCLUSION

Fingerprint classification is a challenging pattern recognition task that has captured the interest of several researches during the last 30 years. A number of approaches and various feature extraction strategies have been proposed to solve this problem. A Feature based flow diagram has been generated which will provide a base for the user to understand the approach used for building the algorithm for fingerprint classification. Using orientation map, singular points can be extracted accurately and their orientations can also be obtained. Benefit of using ridgeline flow is that it can be extracted from poor quality images and it is independent of singular points. Transforms are also used for feature extraction as it highlights the shape of the features. Each feature stated above provides some meaningful information for fingerprint classification; hence a combination of these features can be used to maximize the accuracy of fingerprint classification.

Various approaches of fingerprint classification like rule based, neural network based, genetic algorithm based, ridge flow based reveals that neural network based classification provides better results compared to other techniques. Neural Network using back-propagation algorithm gives good results as it learns complex relationship but it consumes a lot of time for training. Neural Network based classification provides better results where efficiency is important.

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