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ORIGINAL ARTICLE

Fingerprint image enhancement and recognition algorithms: a survey

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Abstract Fingerprint systems have received a great deal of research and attracted many researchers' effort since they provide a powerful tool for access control and security and for practical applications. A literature review of the techniques used to extract the features of fingerprint as well as recognition techniques is given in this paper. Some of the reviewed research articles have used traditional methods such as recognition techniques, whereas the other articles have used neural networks methods. In addition, fingerprint techniques of enhancement are introduced.

Keywords Pattern recognition · Minutiae · Pattern matching · AFIS · Image enhancement · Fingerprint

1 Introduction

1.1 Background

In the world today, fingerprint is one of the essential variables used for enforcing security and maintaining a reliable identification of any individual. Fingerprints are used as variables of security during voting, examination, operation of bank accounts, among others. They are also used for controlling access to highly secured places such as offices, equipment rooms, control centers and so on [1]. Fingerprint training procedures are time-intensive and slow. Furthermore, demands imposed by the painstaking attention needed to visually match the fingerprints of varied qualities, tedium of the monotonous nature of the work and increasing workloads due to a higher demand on fingerprint recognition services, which all prompted the law enforcement agencies to initiate research into acquiring fingerprints through electronic media and automated fingerprint recognition based on the digital representation of fingerprints. These efforts led to the development of automatic fingerprint identification systems (AFIS) over the past few decades. Law enforcement agencies were the earliest adopters of the fingerprint recognition technology; more recently, however, increasing identity fraud has created a growing need for biometric technology for person recognition in a number of nonforensic applications [2].

1.2 Fingerprint individuality

Most of the early fingerprint individuality assessments typically focused on a predominantly minutiae-based representation; some studies explicitly factored in fingerprint class (e.g., right loop, left loop, whorl, arch, tented arch) information. The type, direction and location of minutiae were the most commonly used features in the early studies. These studies estimated the distinctiveness of the entire fingerprint (total pattern variation). These total pattern variation–based fingerprint individuality estimates will be referred to as the probability of fingerprint configuration. A list of the early studies is presented.

Pankanti et al. [3] addressed the fingerprint individuality by quantifying the amount of information available in minutiae points to establish a correspondence between two fingerprint images. They derived an expression that estimates the probability of falsely associating minutiae-based representations from two arbitrary fingerprints.

Orsag and Drahansky [4] discussed the design of a biometric security system based on the fingerprint and speech technology. The biometrics security systems and a concept

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of the integration of both technologies are introduced in their work. Then, the fingerprint technology followed by the speech technology is shortly described. They used a private cryptographic key and hash functions calculated upon the biometric attribute feature (i.e., fingerprint of voice). The hash value is then compared with the stored hash values. If a hash value matches, then the biometric vector, from which the hash value was calculated, is said to be the right vector to decipher corresponding part of the whole cryptographic key. As soon as all parts of the private cryptographic key are deciphered successfully, it is possible to merge them into a single key and use this key to encipher/decipher some data. They used the fingerprint and voice technologies to ensure the security.

2 Fingerprint techniques of enhancement

The quality of the fingerprint images greatly affects the performance of the minutiae extraction. In order to improve the performance of the system, many researchers put efforts into the image enhancement algorithms. The main of those are as follows: Yang et al. [5] proposed filtering design method for fingerprint image enhancement primarily inspired from the traditional Gabor filter (TGF). They state that the previous fingerprint image enhancement methods based on TGF banks have some drawbacks in their image-dependent parameter selection strategy, which leads to artifacts in some cases. To address this issue, they have developed an improved version of the TGF called the modified Gabor filter (MGF). Its parameter selection scheme is image-independent.

Hong et al. [6] presented a fast fingerprint enhancement algorithm that can adaptively improve the clarity of ridge and furrow structures of input fingerprint images based on the estimated local ridge orientation and frequency. They evaluated the performance of the image enhancement algorithm using the goodness index of the extracted minutiae and the accuracy of an online fingerprint verification system.

Zorita et al. [7] presented a complete algorithmic scheme for automatic fingerprint recognition. The whole recognition process is accomplished in two stages: in the first one, biometric characteristics of fingerprints are extracted (characteristics denoted as minutiae which represent basically the beginning end or bifurcation of a ridge), and in the second stage, those fingerprints are matched with templates belonging to the test database. In this article, some alternatives that improve the first stage, namely the image enhancement process, are proposed, consequently leading to an increase in the reliability in the minutiae extraction stage.

Keun et al. [8] outlined a fingerprint enhancement algorithm based on a directional filter bank proposed. The algorithm decomposes a fingerprint image into directional sub-band images in the analysis stage, processes the sub-band images in the processing stage and reconstructs them as the enhanced image in the synthesis stage. Experiment results show that the proposed method reduces the influence of noise on the ridges and valleys, enhances the ridges' moving shape and preserves the spatial characteristics at minutiae and singular points.

Sen and Yangsheng [9] presented a new method of filtering to enhance fingerprint in the singular point area. First, they distinguished the singular point area. Then, they designed a new filter to enhance this area. Experiment results show that their enhancement algorithm is capable of improving both the quality of fingerprint image and the accuracy of the minutiae extraction and that the time required for their algorithm is reduced.

Yun et al. [10] proposed an adaptive processing method that extracts five features from the fingerprint images, analyzes image quality with Ward's clustering algorithm and enhances the images according to their characteristics. If the adaptive processing according to the fingerprint image characteristics is applied in the image enhancement step, the system performance would be more robust. Khan et al. [11] proposed a decimation-free directional filter bank (DFB) structure, which provides output in the form of directional images as opposed to directional sub-band provided in previous DFBs. They stated that the directional images facilitate any further spatial processing if needed. However, preparation of a fingerprint image before it can be given as input to the proposed DFB structure is required due to the fact that fingerprints acquired are of low contrast. The preparation steps involve removing nonuniform illumination from the image. Then, the proposed DFB structure outputs directional images. The final enhanced result is constructed on a block-by-block basis by comparing energy of all the directional images and picking one that provides maximum energy.

3 Fingerprint techniques of feature extraction

Maio and Maltoni [12] used extract minutiae directly from gray-level fingerprint images. Their algorithm is based on a gray-level ridge tracing, which extracts ridges by sequentially following each gray-level ridge until it ends or bifurcates. Their algorithm does not binarize the gray-level fingerprint image directly when conducting minutiae extraction, but binarization is still conducted implicitly by the gray-level ridge tracer.

Bernard and Manzanera [13] developed a fully parallel iterative thinning algorithm called MB2. They claim that it favourably competes with the best known algorithms regarding homotopy, mediality, thickness, rotation invariance and noise immunity, while featuring a speed improvement by a factor two or more owing to a smaller number of operations to perform. Their results show that the MB2 is grounded on a simple physics-based thinning principle that conveys quality, efficiency and conceptual clarity. It is particularly suited to data parallel execution.

Blayvas et al. [14] handled the problem of binarization of gray-level images acquired under nonuniform illumination. They state that earlier work of Yanowits and Bruckestein proposed to construct a threshold surface by interpolating the image gray levels at the points where the image gradient is high. The rationale is that high image gradient indicates probable object edges, and the image values are between the object and the background gray levels. The threshold surface was determined by successive over-relaxation as the solution of the place equation. Hence, their work proposes a different method to determine an adaptive threshold surface. In their new method inspired by multiresolution approximation, the threshold surface is constructed with considerable lower computational complexity and is smooth, yielding faster image binarization and better visual performance.

Sen et al. [15] presented useful and effective fingerprint image segmentation. They extract two new features with which their algorithm can distinguish noisy area from the foreground and therefore reduce the number of false minutiae. They use supervised RBF neural network to classify patterns and select typical patterns to train the classifier. Their experimental results show a significant improvement in fingerprint segmentation performance.

Bazen and Otterlo [16] show that reinforcement learning can be used for minutiae detection fingerprint matching. Minutiae are characteristic features of fingerprints which determine their uniqueness. Classical approaches use a series of image processing steps for this task, but lack robustness because they are highly sensitive to noise and image quality. They propose a more robust approach in which an autonomous agent walks around in the fingerprint and learn how to follow ridges in the fingerprint and how to recognize minutiae. The agent is situated in the environment and uses reinforcement learning to obtain an optimal policy.

Rahimi et al. [17] presented a novel algorithm for the detection of singular points (core and delta points) in fingerprint images. The number and location of singular points are used to classify fingerprint images into five general groups and therefore to narrow down the search space in a large fingerprint database. Using the proposed directional masks in the fist step, they detect the neighborhood of the singular points. In the second stage, using the proposed algorithm, an adaptive singular point detection method is implemented to extract the exact location of core and delta points. In their findings, they stated that a good minutiae extrication algorithm should efficiently incorporate local ride orientation into ridge extraction operation. However, it should also be kept in mind that directional smoothing is usually a computationally expensive operation. Postprocessing is a very important step in minutiae extraction, which can eliminate a significant number of errors.

4 Fingerprint analysis and classification

Fingerprint classification provides an important indexing mechanism in a fingerprint database. An accurate and consistent classification can greatly reduce fingerprint matching time for a large database. Hybrid approaches combine two or more approaches for classification. These approaches show some promise but have not been tested on a large database. For example, Fits and Green [18] used frequency-based approach on 40 fingerprints. They used the frequency spectrum of the fingerprints for classification, whereas Kawagoe and Tojo [19] used another structure-based approach on 94 fingerprints. Vhong et al. [20] reported results on 89 fingerprints in a structure-based approach that used B-spline curves to represent and classify fingerprints. Recently, Cappelli et al. [21] proposed a fingerprint classification algorithm based on the multispace KL transform applied to the orientation field. In that algorithm, the number of classes is denoted by C, the classification accuracy is denoted by Acc, and reject rate is denoted by RR. The classification accuracies reported by the different authors are not different in databases with different numbers of fingerprints, and therefore, they cannot be directly compared. Most of the work in fingerprint classification is based on supervised learning and discrete class assignment using knowledge-based features.

Bernard et al. [22] proposed the use of Kohonen topologic map for fingerprint pattern classification. The learning process takes into account the large intraclass diversity and the continuum of fingerprint pattern types. Depending on the fingerprint domain-specific knowledge and the expert approach, they presented an original and intuitive description of the algorithm. They concluded that the self-organizing maps are efficient in fingerprint classification and provided a good nonlinear bidimensional approximation of a direction-map distribution of feature space.

5 Fingerprint verification techniques

The distinctiveness of a fingerprint can be determined by the overall pattern of ridges and valleys as well as the local ridge anomalies (minutiae points). The existing popular fingerprint matching techniques can be broadly classified into two categories: (a) minutiae-based and (b) correlation-based. The minutiae-based techniques typically match the two minutiae sets from two fingerprints by first aligning the two sets and then counting the number of minutiae that match. Correlation-based techniques match the global pattern of ridges and furrows to see whether the ridges align. The simplest technique is to align the two fingerprint images and subtract the input from the template to see whether the ridges correspond.

The fingerprint matching algorithms are classified based on the alignment assumed between the template and the input fingerprint features. The rotation is denoted by R, the translation is denoted by T, and the scale is denoted by S.

Sagar et al. [23] presented an approach of fingerprint identification based on fuzzy logic techniques. Since the whole procedure of the fingerprint verification systems is very computationally expensive and hence requires more expensive hardware to meet the response-time requirements, they developed a matching algorithm that encodes the detected minutiae points in a compressed format initially, and a fuzzy approximation theorem is employed to match these encoded data with the fingerprint under test. This algorithm has the advantage of being simple and less expensive.

Jain and Pankanti [24] described the design and implementation of a prototype automatic identity authentication system that uses fingerprints to authenticate the identity of an individual. They developed an improved minutiae extraction algorithm claimed to be faster and more accurate than earlier algorithms. An alignment-based minutiae matching algorithm is proposed. This algorithm is capable of finding the correspondences between input minutiae and the stored template without resorting to exhaustive search and has the ability to adaptively compensate for the nonlinear deformations and inexact transformations between an input and template. Both the MSU and the NIST 9 fingerprint databases were used to evaluate the performance of the system.

Sagar and Beng [25] investigated the fusion of fuzzy logic and neural network technology in automated fingerprint recognition for the extraction of important fingerprint features. Their results showed that, on average, the fuzzy neural approach is a better alternative. The hybrid model—fuzzy and neural networks model—performs the minutiae extraction in two stages: a fuzzy front-end and neural back-end. They concluded that by using such fuzzy neural hybrid model, the fingerprint minutiae extraction is more accurate since fewer false minutiae are identified and more true minutiae identified.

6 Patten recognition and neural networks

Blumenstein and Verma [26] presented a description of an implemented system for the recognition of printed and handwritten postal addresses, based on artificial neural networks (ANNs). Two classification methods are compared for the task of character and address recognition. They compared two neural network techniques, measuring recognition rate and accuracy. Their results show the superiority of backpropagation ANNs for the classification of printed and handwritten postal addresses. For printed addresses, the recognition rates are extremely high. Perfect classification rates are obtained when using fonts the ANN had been trained with. High results were also attained for the recognition of addresses using fonts the ANN had not been previously trained with.

Ridder et al. [27] studied the applicability of neural networks to nonlinear image processing problems. As an example, the Kuwahara filtering for edge-preserving smoothing is used in this article because of its nonlinear nature and natural modularity. A number of modular networks were constructed and trained, incorporating prior knowledge in various degrees, and their performance was compared to standard feed-forward neural networks (MLPs). The main conclusion is that neural networks can be applied to nonlinear image processing problems, provided that careful attention is paid to network architecture training set sampling and parameter choice.

Backer [28] examined unsupervised statistical pattern recognition. It is divided into two parts. In the first part of this work, feature extraction and dimensionality reduction are investigated. Several nonlinear reduction techniques are evaluated. In the second part, classification is considered and new adaptive clustering techniques are proposed. Texture images and multispectral images are used because these particular applications tend to generate a high-dimensional feature space. The concept of competitive learning was expanded with three concepts: first, a frequency sensitivity to resolve the known problem that small clusters are put at a disadvantage compared with the large ones. By using the update frequency in the distance calculations, most of these problems can be canceled out. Also, the efficiency is shown to increase with increasing dimensionality or with decreasing number of points. Secondly, a new learning rule for elliptical cluster shapes is introduced where the Mahalanobis distance measure is incorporated into the learning rule. This rule is useful only because of the possibility to immediately update the inverse covariance matrices. Thirdly, the clustering procedures were extended from hard clustering to fuzzy versions by using the so-called fuzzy membership values. All three techniques are combined in a frequency-sensitive fuzzy elliptical competitive learning algorithm.

7 Fingerprint recognition with neural networks

In this section, a review on neural networks applications in image processing is presented. Qian et al. [29] developed a hybrid system consisting of order statistic filters for noise removal and Hopfield networks for deblurring (by optimizing a criterion function). The modulation transfer function had to be measured in advance. They showed that the Hopfield networks become an interesting alternative to conventional optimization techniques when the latter fail in solving the problem either because of its nonlinear character or because of the computational complexity. Chandresakaran et al. [30] used a feed-forward architecture to classify an input window as containing an edge or not. The weights of the network were set manually instead of being obtained from training. A straightforward application of regression of feed-forward ANNs trained to behave like edge detectors was reported by them.

Chua and Yang [31, 32] used cellular neural networks (CNNs) for image processing. CNN is a system in which nodes are locally connected; each node contains a feedback template and a control template, which, to a large extent, determine the functionality of the network. For noise suppression, the templates implement an averaging function for edge detection of a laplacian operator. The system operates locally, but multiple iterations allow distributing global information throughout the nodes.

Maio and Maltoni [33] presented a new approach to minutiae filtering based on neural networks. The minutiae neighborhoods are extracted and normalized with respect to rotation and scale, and their dimensionality is reduced via KL transform. A neural classifier whose topology has been designed to exploit the minutiae duality is employed to perform the neighborhoods classification. They summarize that the filtering method proposed in their work, in spite of a certain increase in dropped errors, determines significant reduction in false and exchange errors. A little computational effort was required by their filtering technique since the average number of minutiae per fingerprint is about 50.

Ridder et al. [34] built a modular feed-forward ANN approach that mimics the behavior of the Kuwahara filter and edge-preserving smoothing filter. Their experiment showed that the mean squared error used in ANN training may not be representative of the problem at hand. Furthermore, unconstrained feed-forward networks often ended up in linear approximation to the Kuwahara filter. Antowiak and Macukow [35] investigated the advantages of optical wavelet transform used as pre-processor for an artificial neural network. They showed by digital simulation that such setup can successfully identify and discriminate complex biometric images such as fingerprints. The achieved capabilities include limited shift-rotation scale and intensity invariance. They also showed that the edge-enhancement filter applied before the wavelet transform significantly improves the abilities of the system.

8 Conclusions

This paper gives an overview of the pattern recognition techniques used in fingerprint recognition systems. In particular, it focuses on the techniques employed for features extraction as well as the most used methods for recognition purpose. In addition, we introduced some enhancement techniques that have been used to improve further the quality of fingerprint recognition systems.

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