Neurocomputing 71 (2008) 1939– 1946

Contents lists available at [ScienceDirect](www.sciencedirect.com/science/journal/neucom)

Neurocomputing

journal homepage: <www.elsevier.com/locate/neucom>

A fingerprint verification algorithm using tessellated invariant moment features

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article info

Available online 3 March 2008

Keywords: Distance Fingerprint matching Fingerprint verification Image-based Invariant moments

ABSTRACT

In this paper, an enhanced image-based fingerprint verification algorithm is proposed to improve matching accuracy and processing speed by overcoming the demerits of previous methods over poorquality images. It reduces multi-spectral noise by enhancing a fingerprint image to accurately and reliably determine a reference point, and then aligns the image according to the position and orientation of reference point to avoid time-consuming alignment. A set of fixed-length moment features, invariant to the affine transform, is extracted from tessellated cells on a region of interest (ROI) centered at the reference point. The similarity between an input and a template in a database is evaluated by eigenvalue-weighted cosine (EWC) distance. Experimental results show that the proposed method has better performance in accuracy and speed comparing with other renowned methods.

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1. Introduction

Fingerprint-based biometrics systems are often used as the automatic fingerprint verification system (AFVS) for criminal identification and police work. In an AFVS, the input includes a user identity (ID) and a fingerprint, and the output indicates whether the input fingerprint is consistent with the ID. The system simply compares the input fingerprint with the one addressed by the ID in the database. The performance of an AFVS in terms of matching accuracy and computation speed depends mainly on methods of feature extraction and matching algorithm. Researches have been extensively explored on feature extraction and matching algorithms, yet these are still challenging for better performance. Fingerprint feature extraction and matching methods may be broadly classified into three categories: minutiaebased, image-based, and hybrid [\[16\]](#page--1-0).

The most popular and widely used methods are minutiaebased [\[10,13\]](#page--1-0). These use a feature vector extracted from fingerprints as sets of points in a multi-dimensional plane. The feature vector may comprise several characteristics of minutiae such as type, position, orientation, etc. A typical minutiae-based method essentially searches for the best alignment between the template and the input minutiae sets. Most minutiae-based methods suffer from several shortcomings. For example, extracting minutiae from a poor-quality fingerprint image may result in low matching accuracy. In addition, these methods may not fully utilize the rich discriminatory information available in the fingerprints with high computational complexity [\[17\]](#page--1-0).

The image-based methods [\[1,11,12,22,27,29\]](#page--1-0), however, use features other than characteristics of minutiae from the fingerprint ridge pattern, such as local orientation and frequency, ridge shape, and texture information. The features for these methods may be extracted more reliably than those of minutiae. They usually require less preprocessing effort than minutiaebased methods using global information from a fingerprint, but they have limited ability to track variations in position, scale, and rotation angle of a fingerprint [\[27\]](#page--1-0). Invariance to an affine transform should be included for matching in order to deal with different input conditions and hence to enhance matching accuracy. Hybrid methods [\[2,18,19,21\]](#page--1-0) using features from both approaches have recently been researched. These methods have mostly the same problems as the minutiae-based methods.

One fine method uses a reference point with some imagebased features [\[11\]](#page--1-0) for fingerprint matching. In this method, the variation in position is canceled by registering the images with respect to a reference point that can be consistently detected in different instances of the same fingerprint. However, this approach exhibits deficiencies of typical image-based methods, which will be discussed in next section.

In this paper, an image-based algorithm using tessellated invariant moment features for fingerprint verification with a reference point is proposed to perform more accurately and in less processing time. It reliably finds a reference point with the proposed preprocessing and uses an alignment of the input image with the template. It also uses invariant moment features that are

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^{0925-2312/\$ -} see front matter \circ 2008 Elsevier B.V. All rights reserved. doi:[10.1016/j.neucom.2007.12.034](dx.doi.org/10.1016/j.neucom.2007.12.034)

invariant to an affine transform to remedy the problems occurred in previous researches, and performs matching.

A fingerprint image is preprocessed to enhance the image by short time Fourier transform (STFT) analysis [\[3\]](#page--1-0). The STFT can be used to analyze the fingerprint image both in space and in frequency, helping to eliminate multi-spectral noise in the image. The algorithm simultaneously estimates all the intrinsic properties of the fingerprints, such as foreground region mask, local ridge orientation, and local ridge frequency, and uses these properties to enhance the fingerprint image.

A reference point is used to align a template and an input fingerprints before applying the local structure for verification. In the proposed algorithm, a global structure, which represents the maximum curvature in an orientation field image, is used to determine a unique reference point for all types of fingerprints including partial fingerprints. The position of the reference point is determined by the complex filtering methods [\[15,20\].](#page--1-0) They find a unique point with the maximum curvature very successfully. The orientation of the reference point is determined by using the least mean square (LMS) orientation estimation algorithm [\[7\],](#page--1-0) which estimates the orientation field using the gradient at each pixel and smoothes it with a Gaussian window.

An ROI centered on the reference point is then determined and tessellated into a predefined number of nonoverlapping square cells in order to minimize the effects of noise and nonlinear distortions. A set of fixed-length features consisting of seven invariant moments is extracted from each tessellated cell to represent the fingerprint as information of the local structure. Fingerprint verification is based on measures of similarity to the eigenvalue-weighted cosine (EWC) distance to match the two corresponding feature vectors of the input fingerprint image and template fingerprint image in the database. Experiments under various conditions have been done to evaluate the performance of the proposed method in terms of accuracy and computation speed, and to compare with other prominent methods using public databases.

The paper is organized as follows. Sections 2 and 3 are for the summary of prior related works and motivation, and a brief review of invariant moments, respectively. In Section 4, the proposed method is explained in detail and its experimental results are discussed in Section 5. Section 6 summarizes the conclusion.

2. Prior related works and motivation

Image-based methods are frequently used for fingerprint recognition. Among various image-based methods, Gabor feature-based methods [\[11,22\]](#page--1-0) present a relatively high matching accuracy by using a bank of Gabor filters to capture both the local and global features. By approximately making the methods rotation-invariant with multiple templates, however, these methods require significantly high processing times with large storage space, and performance degradation from the approximation.

Hybrid fingerprint matching schemes [\[2,21\],](#page--1-0) based on both minutiae and feature maps, utilize merits from both approaches. However, it is very difficult to accurately detect all minutiae, which may significantly affect the robustness of these approaches. Moreover, the computation requirement for the feature maps extracted from the entire image or features on each minutia with Gabor filters becomes very high.

Transform-based methods using digital wavelet transform (DWT) features [\[27\]](#page--1-0) or digital cosine transform (DCT) features [\[1\]](#page--1-0) show a high matching accuracy for inputs identical to templates on its database. However, these methods have not considered the invariance to an affine transform to deal with different input conditions. Another method with the integrated wavelet and Fourier-Mellin transform (WFMT) [\[12\]](#page--1-0) uses multiple WFMT features to deal with the variability of input fingerprint images. This method, however, is not suitable for all types of fingerprint images by choosing a core point as reference point.

In our previous work [\[29\],](#page--1-0) the fingerprint verification using invariant moments with the learning vector quantization neural network is proposed. It shows some merits, but, using features from the fixed-size ROI may lead to mismatching if the detected reference point is located near the border of a fingerprint image.

In order to improve matching accuracy and computational complexity on images generated under various input conditions, we focus on the design of an effective algorithm with techniques to eliminate or reduce the disadvantages occurred in previous researches. These techniques, listed below, are implemented in five sequential modules in the proposed algorithm.

- (1) Tessellated invariant moment features are used for fingerprint verification. The invariant moment features provide scale, position, and rotation invariance and can be computed algebraically from tessellated cells.
- (2) A preprocessing with STFT can remove multi-spectral noises while enhancing structural information in images, and hence help to find a reference point accurately and reliably.
- Before extracting moment features from tessellated cells, the input image is rotated to make the orientation of the reference point to zero. With the rotation centered at the reference point, time-consuming alignments for rotation and translation become simple and even improve the matching accuracy.
- (4) Extracting invariant moment features from nonoverlapping tessellated cells significantly reduces the effects from noise and nonlinear distortions, and thus better preserves the local information.
- (5) By adjusting the size of ROI and the number of the cells, we can capture the local and global structure information better around the reference point.
- (6) By assigning different weights to each tessellated cell, the algorithm can deal with the cases that a reference point is located near the rim of the fingerprint image.
- (7) Fixed-length vectors are used to represent moment features and it can reduce the computation load. Overall feature extraction and matching to a template are much faster comparing with the transform-based methods.

3. Invariant moments

Moment features used in this paper can provide the properties of invariance to scale, position, and rotation [\[6\]](#page--1-0). We used moment analysis to extract invariant features from tessellated cells in an ROI. This section gives a brief description of the moment analysis.

For a 2-D continuous function $f(x, y)$, the moment of order $(p+q)$ is defined as:

$$
m_{pq} = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x^p y^q f(x, y) \, dx \, dy \quad \text{for } p, q = 0, 1, 2, ... \tag{1}
$$

A uniqueness theorem states that if $f(x, y)$ is piecewise continuous and has nonzero values only in a finite part of the xy-plane, moment of all orders exist, and the moment sequence (m_{pq}) is uniquely determined by $f(x, y)$. Conversely, (m_{pq}) is uniquely determined by $f(x, y)$.

The central moments are defined as:

$$
\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \bar{x})^p (y - \bar{y})^q f(x, y) \, dx \, dy \tag{2}
$$

where $\bar{x} = (m_{10}/m_{00})$ and $\bar{y} = (m_{01}/m_{00})$.

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