A Filterbank-based Representation for Classification and Matching of Fingerprints*

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Biometric identification (or biometrics, in short), which refers to identifying an individual based on his or her distinguishing physiological and/or behavioral characteristics (biometric identifiers) [1], associates/disassociates an individual with a previously determined identity/identities based on "how she is or what she does". Because many physiological or behavioral characteristics are distinctive to each person, biometric identifiers are inherently more reliable and more capable than knowledge-based and token-based techniques in differentiating between an authorized person and a fraudulent impostor. Currently, there are a multitude of biometric techniques either widely used or under investigation. These include, facial imaging (both optical and infra-red), hand and finger geometry, eye-based methods (iris and retina), signature, voice, vein geometry, keystroke, and finger- and palm-print imaging.

Fingerprints are one of the most mature biometric identifiers and are considered legitimate identity proofs of evidence in courts of law all over the world. Fingerprints are, therefore, used in forensic divisions worldwide for criminal investigations. More recently, an increasing number of civilian and commercial applications are either using or actively considering to use fingerprint-based identification because of a better understanding of fingerprints as well as its superior demonstrated matching performance than any other existing biometric technology.

The features used by the current fingerprint-based identification systems have evolved from the intuitive designs geared for manual (visual) use for fingerprint experts. It is not clear whether the use of these features and philosophies underlying the identification systems heavily tuned for human use are as effective for fully automatic processes. Nor do we know whether identification technologies inspired and used by the humans are capable of taking full advantage of all the discriminatory information available in the fingerprints. Furthermore, the conventionally used exclusively global/local approaches to fingerprint representations tend to restrict either the scope of their application or do not easily lend themselves to indexing mechanisms. Consequently, there is a need to explore novel and generic representations of fingerprints motivated from computer vision and pattern recognition perspective. The work presented here is one such candidate representation of fingerprint under research investigation.

We view fingerprints as oriented texture pattern, textures which exhibit an inherent and well-defined sense of directionality. We argue that for sufficiently complex oriented textures such as fingerprints, invariant texture representations can be extracted combining both global and local discriminatory information in the texture. Given a fingerprint image, we demonstrate that reliable translation and rotation invariant representations can be built based entirely on the inherent properties of the underlying fingerprint texture. We further illustrate that the representations thus derived are useful for robust discrimination of the fingerprints. In particular, we will present the application of our novel representation scheme for solving the problems of fingerprint classification [2]

*Based on condensation of our previously published works [2, 3].

and matching [3] on large datasets of fingerprint images acquired in real situations.

The proposed scheme of generic representation for oriented textures relies on extracting one or more invariant frames of reference of the oriented texture based on an analysis of its orientation field. A predetermined region of interest around the origin of each frame of reference is tessellated into cells. Each cell is then examined for the information in one or more different, possibly orientation specific, spatial frequency channels. An ordered enumeration of the features thus extracted from each cell is used as the representation of the texture. (i) The number of frames of references, (ii) the extent and the shape of the region of interest, (iii) the specific tessellation scheme, the nature, the number, and the characteristics of bandpass filters, and (iv) the features extracted from each cell are dictated by the specifications of the application domain. Depending on the application domain, there may be specific pre- and post-processing methods involved to normalize structural and statistical artifacts peculiar to the domain-specific image acquisition modality.

The above mentioned generic framework for representation is tuned to the fingerprint domain to obtain fingerprint features. Our fingerprint feature extraction scheme first determines a reference frame in the fingerprint image and a circular region around the reference frame origin is defined as the region of interest; the region of interest is divided into sectors; each sector is normalized to a constant mean and variance and filtered using a bank of Gabor filters to produce a set of filtered images; grayscale variance in a sector quantifies the underlying ridge structures and is defined as a feature. A feature vector, which we call FingerCode, is the collection of all the features (for every sector) in each filtered image. Thus, the feature elements capture the local information and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The proposed representation for the fingerprints which yields a relatively short, fixed length (640-byte) FingerCode, is suitable for classification as well as matching.

The fingerprint classification is based on a two-stage classifier which uses a K-NN classifier in its first stage and a set of neural network classifiers in its second stage. The classification algorithm is tested using the NIST-4 database contains 800 fingerprints from each of the five fingerprint classes; a total of 4000 fingerprint images from 2000 different fingers. We trained our two-stage classifier on the first 2000 fingerprint images. The classifier is able to achieve an accuracy of 90% on the remaining 2000 fingerprint images.

Fingerprint matching is a much more complex problem and imposes more demands on discriminatory invariant information in the features. Our fingerprint matching algorithm is based on the Euclidean distance between the two corresponding FingerCodes and hence is extremely fast and scalable. For matching, we used a database of 167 people (2572 prints) acquired using an on-line scanner in our lab. We are able to achieve an identification accuracy which is marginally inferior to the best results of minutiae-based algorithms published in the open literature [4]. Our system performs better than a state-of-the-art minutiae-based system when the false accept rate requirement of the application system is not very low. We obtained a significant performance improvement of a typical minutiae-based matcher [4] by combining it with the filterbank-based matcher and illustrate that FingerCode captures information that is complementary to that used by a minutiae-based fingerprint matcher.

We strongly believe that a significantly better performance can be achieved using our framework for representation by addressing the following issues: (i) a more robust determination of the reference frame, (ii) better tessellation schemes, (iii) refinements of initial strategies for feature extraction and matching, and (iv) indexing techniques based on the proposed representation. These issues constitute topics of our ongoing research investigations.

References

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