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A fingerprint retrieval system based on level-1 and level-2 features

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ABSTRACT

This paper proposes a novel fingerprint retrieval system that combines level-1 (local orientation and frequencies) and level-2 (minutiae) features. Various score- and rank-level fusion strategies and a novel hybrid fusion approach are evaluated. Extensive experiments are carried out on six public databases and a systematic comparison is made with eighteen retrieval methods and seventeen exclusive classification techniques published in the literature. The novel approach achieves impressive results: its retrieval accuracy is definitely higher than competing state-of-the-art methods, with error rates that in some cases are even one or two orders of magnitude smaller.

1. Introduction

Automatic fingerprint identification systems are used in forensic and government applications to handle populations of several millions individuals (Maltoni, Maio, Jain, & Prabhakar, 2009; Ratha & Bolle, 2003; US-VISIT Program, 2011) or even more than one billion, as in the Indian Unique Identity Project (Unique Identification Authority of India, 2011). When the goal is to accurately and efficiently compare a query fingerprint against a huge database, it is desirable to reduce the number of fingerprints to be considered by using fingerprint retrieval (pre-filtering) techniques (Cappelli, Maio, & Maltoni, 2000; Maltoni et al., 2009). These techniques can be divided into two main categories: (i) exclusive classification and (ii) continuous classification (or fingerprint indexing) (Cappelli & Maio, 2004; Maltoni et al., 2009).

Exclusive classification techniques (Candela, Grother, Watson, Wilkinson, & Wilson, 1995; Cappelli & Maio, 2004; Cappelli, Maio, Maltoni, & Nanni, 2003; Hong & Jain, 1999; Shah & Sastry, 2004) partition the database into a fixed number of classes: during the identification phase, the query fingerprint is compared only to fingerprints belonging to the same class. Techniques belonging to this category are often not able to sufficiently narrow down the search due to (i) the small number of classes and (ii) the unevenly distribution of the fingerprints among them. This led the scientific community to investigate retrieval systems that are not based on exclusive classes, but represent each fingerprint in a robust and stable manner so that, in the search phase, it is possible to quickly select a reduced list of the most similar candidates according to an appropriate metric (Cappelli, Maio, & Maltoni, 1999; Cappelli et al., 2000; Germain, Califano, & Colville, 1997; Jiang, Liu, & Kot, 2006; Lumini, Maio, & Maltoni, 1997). Only such candidates are then compared to the query fingerprint using an automated matching algorithm to produce the identification result (or a shorter candidate list to be finally examined by a human expert).

This paper proposes a novel fingerprint retrieval method that combines level-1 (local ridge-line orientations and frequencies) and level-2 (minutiae positions and angles) features. Extensive experiments on six public databases show that the proposed technique markedly outperforms state-of-the-art methods.

The rest of this paper is organized as follows. Section 2 describes the proposed feature extraction steps; Section 3 introduces the similarity measures and the fusion strategies. In Section 4, experiments on six public datasets compare the novel approach with several state-of-the-art competing techniques. Finally Section 5 draws some conclusions.

2. Feature extraction

A fingerprint is the representation of the epidermis of a finger: it consists of a pattern of interleaved ridges and valleys (Fig. 1(a)) (Maltoni et al., 2009). Ridges and valleys often run in parallel; sometimes they bifurcate and sometimes they terminate. Fingerprint features are generally described in a hierarchical order at three levels: level-1 (pattern), level-2 (minutiae points) and level-3 (pores and ridge shape).

- Level-1: when analyzed at the global level, fingerprint patterns can be characterized by two main features: local orientations (Fig. 1(b)) and local frequencies (Fig. 1(c)). The local orientation at a given position (x,y) is the angle θ_{xy} that the fingerprint ridges forms with the horizontal axis. The local frequency f_{xy} at point (x,y) is the number of ridges per unit length along a

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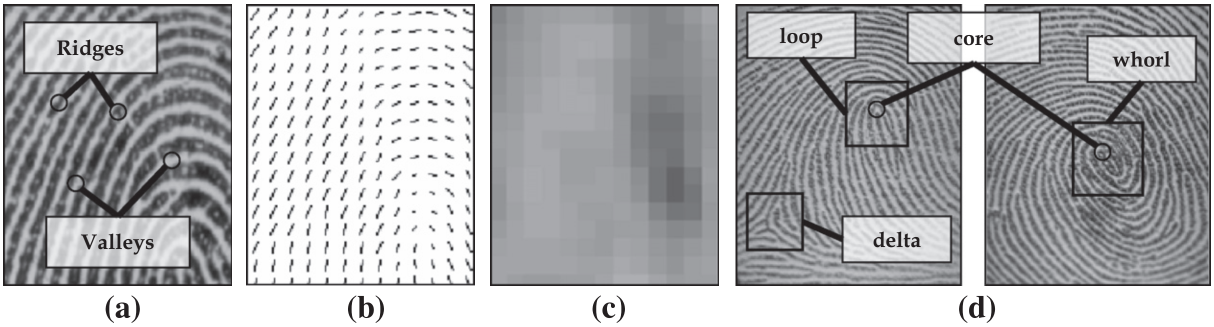

Fig. 1. Ridges and valleys in a fingerprint image (a); local orientations (b); local frequencies (darker blocks denote lower frequencies) (c); singular regions and core points (d).

hypothetical segment centered at (x,y) and orthogonal to the local orientation θ_{xy}. Furthermore, at this level, the pattern may exhibit one or more regions where the ridge lines assume distinctive shapes. These regions (called *singularities* or *singular regions*) may be classified into three typologies: *loop*, *delta*, and *whorl* (see Fig. 1(d)). Singular regions belonging to loop, delta, and whorl types are characterized by $\cup$, Δ, and O shapes, respectively. The *core* point (used by some algorithms to pre-align fingerprints) corresponds to the center of the north (upper) most loop type singularity.

- Level-2: at the local level, other important features, called *minutiae* can be found in fingerprint patterns. Minutiae refer to various ways that the ridges can be discontinuous. For example, a ridge can abruptly come to an end (termination), or can divide into two ridges (bifurcation) (Fig. 2(a)). Although several types of minutiae can be considered, usually only a coarse classification (into these two types) is adopted (Maltoni et al., 2009).
- Level-3: at the very local level, further small details can be found in fingerprint patterns. They include sweat pores, dimensional attributes of the ridges (e.g., width, shape, edge contour), incipient ridges, breaks and scars (Fig. 2(b)). Although level-3 features are distinctive and important for latent fingerprint examiners (Maltoni et al., 2009), their reliable detection requires good quality fingerprints and high resolution scanners (at least 1000 dpi).

Given a fingerprint image, the proposed approach extracts level-1 and level-2 features by performing the following steps (Fig. 3).

1. The fingerprint pattern is segmented from the background using the approach proposed in Maio and Maltoni (1997), which is based on the block-based average magnitude of the gradient (Fig. 3(1)).
2. The traditional gradient-based technique (Ratha, Chen, & Jain, 1995) is applied to estimate the local orientations every 16 pixels along the horizontal and vertical axes (orientation image), using an averaging window of 17 $\times$ 17 pixels. Each estimated orientation element consists of an angle $\theta \in [0, \pi[$ and a value $s \in [0, 1]$ denoting the reliability (strength) of the estimation (in Fig. 3(2), the strength is represented by the length of the segment denoting each orientation).
3. Once local orientations are available, they are used to estimate local ridge-line frequencies, at the same image locations, as described in Hong, Wan, and Jain (1998) (frequency image). Each frequency element is a value $f \in \mathbb{R}$, denoting the inverse of the average ridge-line period estimated in a neighborhood (in Fig. 3(3), light blocks denote higher frequencies).
4. The local orientations are also used to find the fingerprint core (Fig. 3(4)). Since this is a critical step, two techniques are adopted: the iterative singularity detection approach described in Karu and Jain (1996) and the approach based on ridge-line normals described in Rerkrai & Areekul, 2000. In case of ambiguities, both the approaches are allowed to propose more candidates (up to five); in the following, $C = \{\mathbf{c} | \mathbf{c} = (x_c, y_c)\}$ denotes the set of candidate cores detected in the current fingerprint ($|C| \leqslant 5$).
5. For each candidate core $\mathbf{c} = (x_c, y_c)$, the orientation image is aligned with respect to (x_c, y_c) and downsampled to one third of its original resolution. As discussed in Cappelli (xxxx), this improves both accuracy and efficiency.
6. Similarly, for each candidate core $\mathbf{c} = (x_c, y_c)$, the frequency image is aligned with respect to (x_c, y_c) and downsampled to one third of its original resolution.
7. The level-1 feature vectors are obtained from the downsampled images, by considering only the elements satisfying the following constraint: $d_x^2 + d_y^2 \leqslant r^2 \wedge d_y \geqslant -1$, where d_x (d_y) is

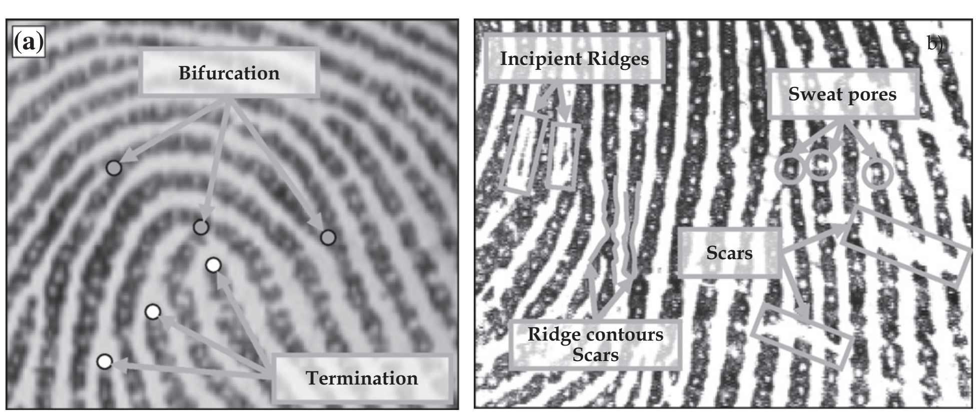

Fig. 2. Termination and bifurcation minutiae in a sample fingerprint (a). Examples of level-3 features in a sample fingerprint acquired at 1000 dpi (b).