# Fingerprint Image Segmentation based on Oriented Pattern Analysis

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Abstract: Segmentation is a crucial task in automatic fingerprint identification systems. This paper describes a novel segmentation approach which takes into account the directional information inherent in fingerprint ridges. The method considers a directional operator to feed a $k$-means unsupervised clustering algorithm that labels the image in non-overlapping regions. Morphological operations are performed to fill holes and properly separate foreground from background. Experiments conducted on Fingerprint Verification Competition (FVC) datasets demonstrate that the proposed method, denoted as Oriented Pattern-based Segmentation (OPS), achieves competitive results when compared to other well-known available fingerprint segmentation approaches.

## 1 INTRODUCTION

There is currently a major concern regarding security, privacy, identification and recognition of people. Simultaneously, automatic fingerprint identification systems (AFIS) have become the most widely used technology for this task (Arora et al., 2015; Ashbourn, 2014; Cao and Jain, 2015; Guesmi et al., 2015; Jain and Hong, 1996; Kasban, 2016; Krish et al., 2018; Li and Jain, 2015; Neumann et al., 2016), due to a number of desirable biometric characteristics: (i) universatility (every person has the characteristic); (ii) permanence (the characteristic should be sufficiently invariant over a long period of time); (iii) collectability (the characteristic should be easily collected and measured quantitatively); (iv) distinctiveness (the characteristic is sufficiently different from one person to another, even in case of identical twins).

Fingerprints are oriented texture patterns created by interleaved ridge and valley information present on the fingertip surface. There are different possible ways to obtain a fingerprint image. Rolling an inked finger on a paper and then scanning this paper was the usual technique. Due to the advances in sensor technology, different fingerprint devices can be used on fingerprint acquisition (Arjona and Baturone, 2014; Cappelli et al., 2002; Hong et al., 1998; Liu et al., 2013; Maltoni et al., 2009). Figure 1 illustrates some fingerprint images acquired from different sensor technologies.

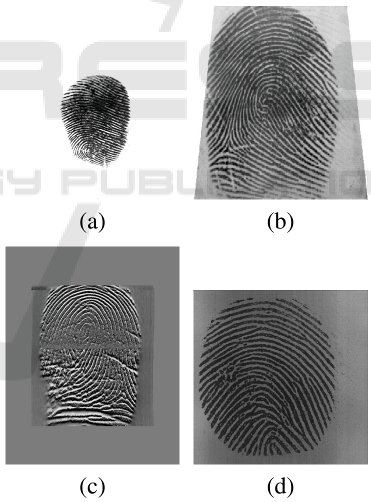

Figure 1: Fingerprint images acquired from different sensor techniques: (a) electric; (b) optical; (c) thermal sweeping; (d) capacitive. Source: Cappelli et al. (2007).

Fingerprint segmentation (Bazen and Gerez, 2001; Chen et al., 2004; Fahmy and Thabet, 2013; Liu et al., 2016; Mehtre et al., 1987; Sankaran et al., 2017; Yang et al., 2015) aims to distinguish foreground regions from the image background, corresponding to an important stage in automatic fingerprint recognition systems. Since fingerprint images can be affected by diverse conditions (such as noise) and acquired by a variety of sensors, segmentation is a very challenging task.



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This work describes and evaluates a novel segmentation approach, denoted as Oriented Pattern-based Segmentation (OPS), which takes into account the directional information present in fingerprint ridges, which is based on an operator used by an unsupervised clustering algorithm to separate the image into non-overlapping regions. Evaluation is performed on four Fingerprint Verification Competition (FVC) (FVC, 2018) datasets to demonstrate the effectiveness of the results.

The text is organized as follows. Section 2 introduces an operator that extracts anisotropic quality information from fingerprint images. In Section 3, the segmentation problem related to these images is addressed. Experimental results are provided in Section 4. Finally, concluding remarks and directions for future work are presented in Section 5.

## 2 DIRECTIONAL INFORMATION OPERATOR

Textural analysis (Jain et al., 2001; Joy and Azath, 2017; Marasco et al., 2018; Marasco and Sansone, 2010) constitutes an important technique for processing images containing directional information, whose magnitude of the corresponding anisotropy should be measured.

This work is particularly interested in a measure of the distance between ridge and valley information in fingerprints. A systematic way to compute such distance is firstly considered within a given neighborhood. Then, a specific fingerprint quality can be set.

Some definitions related to the particular neighborhood considered in this work are initially introduced. Let $\Gamma$ be a sliding window of size $M \times N$ (usually, $M = N = (2l+1)$, $l \in \mathbb{Z}$) of an image $f(x,y)$, $f : (x,y) \in \mathcal{D}_f \subset \mathbb{Z}^2 \mapsto \mathbb{Z}$. Moreover, let $D$ be the number of considered directions in $\Gamma$, and $n$ the corresponding number of pixels in a given direction.

In this work, these pixels are referred to as *test points*. It is worth noticing that, in order to represent all $D$ directions in a two-dimensional grid, the number $n$ of test points has a minimum bound, that is, for any $n \geq 2$, we can define up to $(2n-2)$ directions.

Thus, given a discrete square grid with $M = N = n$ and the origin $(0,0)$ located at its upper left corner, the coordinates $(x,y)$ of the $n$ test points, in a given direction $\alpha$, are computed as:

$$\begin{aligned} x &= x_{center} + p\cos(\alpha) \\ y &= y_{center} - p\sin(\alpha) \end{aligned} \quad (1)$$

for all $p$ such that $-n/2 \leq p \leq n/2$. Moreover, $x_{center}$ and $y_{center}$ are the coordinates of the point containing the sliding window $\Gamma$ centered in this location. Figure 2 shows an example of test points for $\alpha = 45°$ and $n = 9$.

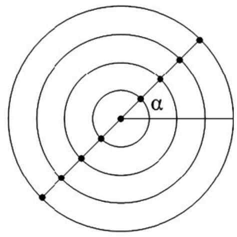



Figure 2: Test points for $\alpha = 45°$ and $n = 9$.

Finally, this neighborhood can be defined as a set $S_i^n$ of $D$ test points with length $n$ and discrete direction $i$, which can easily be computed by repeating the above procedure for all $D$ directions ($i \in \{0, 1, ...D-1\}$), by respectively changing the value of $\alpha$ accordingly ($\alpha = 0,\ 1 \cdot 180/D,\ 2 \cdot 180/D, ..., (D-1) \cdot 180/D$).

In this approach, it is assumed that, in the aforementioned neighborhood, the physics of the image acquisition imposes certain arrangements on the image gray levels. That is the case, for example, of the image points associated with two distinct regions: one which is parallel and the other perpendicular to the flow orientation contained in an intensity pattern created by some anisotropic process (Kass and Witkin, 1987).

Under such conditions, it can be observed a strong statistical relationship between the gray levels along the flow orientation and, by contrast, gradual changes causing this relationship to weaken along the corresponding perpendicular orientation. These aspects reveal a direct connection between the anisotropy and particular combinations of distinct random variables around of these regions.

For the sake of simplification, this work borrows and adapts the formalism presented by Oliveira and Leite (2008), whose approach used oriented information to reconnect broken ridges. Here, it is used to measure quality. Therefore, the abstract idea behind this quality index consists in analyzing samples drawn from these two image regions in order to quantify the difference that makes the anisotropy distinguishable.

The main steps of the proposed operator are described as follows. Figure 3 shows some results produced through this process.

- Consider $f$ as input image, $S$ representing the neighborhood and $D$ as the number of considered directions. Different amounts of test points and directions can be set up in accordance with a certain scale and resolution for a given image. On the other hand, several quality and information crite-

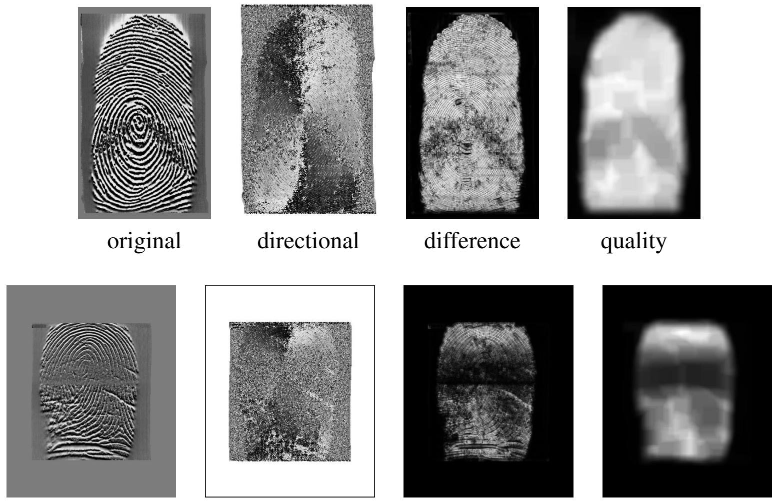



Figure 3: Fingerprint image operator process.

ria can be considered to express separability (or contrast), variability, homogeneity, completeness, entropy and so forth;

- Compute standard deviation (or other information parameter as mean, moments of higher orders, among others) on this neighborhood $S$ for each of the $D$ directions;
- The information associated with each direction $i$ is compared to the one obtained from another direction $j$, $i \neq j$. Once perpendicular direction pairs are sufficient to characterize orientated patterns. Thus, the predominant orientation information is obtained;
- The pair of directions $i$ and $j$ exhibiting the highest information contrast in a given pixel, defines the local orientation (directional) image.

The problem of fingerprint image segmentation based on pixel-wise quality is discussed in the next section.

# 3 PROPOSED FINGERPRINT IMAGE SEGMENTATION

The segmentation method proposed in this work is composed of the following steps: (i) *fingerprint quality analysis*: this step estimates the local quality of the input image; (ii) *mathematical morphology transformation*: some morphological transformations are applied to attenuate local discrepancies; (iii) *unsupervised classification*: the $k$-means clustering process is performed on the attenuated image to find markers (pixels) corresponding to regions with different quality; (iv) *image segmentation by watershed*: a segmented image is obtained through the application of watershed influence zones.

This work considers fingerprint pattern as a regular anisotropic texture. There is a certain regularity on the ridge and valley information. The gray levels in a perpendicular direction to the ridge-valley structure can be modeled as smoothed sinusoidal signals. Similarly, despite the gradual changes on ridge and valley gray levels, there is a certain homogeneity of the pixels along their parallel orientations.

For directional field estimation, this method uses *variance* to express homogeneity of each $S_i$. In such a case, a pair of directions exhibits the highest contrast information and defines the directional image $O$ as follows:

$$O(x,y) = \begin{cases} i, & \text{if } \sigma^2(S_i(x,y)) < \sigma^2(S_i + \frac{D}{2}(x,y)) \\ i + \frac{D}{2}, & \text{if } \sigma^2(S_i(x,y)) \geq \sigma^2(S_i + \frac{D}{2}(x,y)) \end{cases}$$

The descriptor expresses the strength of the information along certain oriented information. The next step is the application of morphological transformations to attenuate discrepancies. Considering this image, a $k$-means clustering algorithm is used to find non-overlapping regions with distinct quality. The parameter $k$ defines the number of regions. Empirically, value $k = 3$ showed the best response.

The centroid values are used as markers and the region with lower value is considered as background. Eventually, holes may exist in the image (background surrounded by foreground) and a watershed transform can be applied successfully. Figure 4 illustrates this process. Original fingerprint images are shown in Figures (a) and (d). There are three non-overlapping regions in Figures (b) and (e), where the background is represented in black color. It can be observed, in (b) and (e), that there is a hole (in black color) in the fingerprint foreground, defined by two regions, one with gray color and the other in white color. This region will disappear after the application of a watershed technique. Figures 4 (c) and (f) show the foreground masks that encompass those regions.

# 4 EXPERIMENTAL EVALUATION

The effectiveness of the proposed segmentation algorithm is verified through four public fingerprint verification competition datasets (FVC2000, FVC2002, FVC2004 and FVC2006) (Cappelli et al., 2007).

Related work on fingerprint image segmentation often validates the corresponding segmented images via their own ground truth. Notwithstanding, there is no public ground truth available for these FVC databases. Ideally, a ground truth should be built by three specialists in order to achieve a consensus.

The final goal of the fingerprint segmentation process is to improve the fingerprint recognition performance. Thus, the assessment of the segmentation algorithm effectiveness should be carried out through a fingerprint recognition test. Recognition performance indicates whether the segmentation algorithm is adequate or not.

Based on this scenario, this work opted for two types of validation: a quantitative and a qualitative one. Two approaches, proposed by Thai and Gottschlich (2016) and Kovesi (2018), were used in the comparison of the results. The first segmentation method decomposes the image into three portions and considers texture and oriented patterns present in the fingerprint. The second one partitions the image into blocks and evaluates the standard deviation in each region; if this value is above a threshold, it is deemed part of the fingerprint.

## 4.1 Fingerprint Databases

The Fingerprint Verification Competition (FVC) took place in 2000, 2002, 2004 and 2006, as an initiative to compare fingerprint matching algorithms. These competitions were organized by the Biometric System Laboratory of the University of Bologna Cappelli et al. (2007), as well as Pattern Recognition and Image Processing Laboratory of the Michigan State University, Biometric Test Center of San Jose State University and, in the last year, Biometrics Research Laboratory of the Universidad Autonoma de Madrid. In this work, 2000, 2002, 2004 and 2006 datasets were used in the experiments to validate the proposed operator based on directional information.

Each FVC dataset contains 4 databases, namely DB1A, DB2A, DB3A and DB4A. The 2000, 2002 and 2004 databases contain 800 fingerprint images (i.e., there are 100 fingers with eight samples). The 2006 dataset contains 4 databases and each one has 1680 fingerprint images (140 individuals have collected 12 samples).

The image size of each dataset is different from one another and the resolution is over 500 dpi. Each database was acquired by different sensor modalities.

Rules have changed from one competition (2004) to another (2006). For 2004, each sample in the subset $A$ is matched against the remaining samples of the same finger to compute the False Non Match Rate (FNMR) (also referred to as False Rejection Rate (FRR)). If matching $g$ against $h$ is performed, the symmetric one (i.e., $h$ against $g$) is not executed to avoid correlation.

The total number of genuine tests (if no enrollment rejections occur) is: ((8*7)/2)*100 = 2,800. The total number of false acceptance tests (False Match Rate (FMR), also referred to as False Acceptance Rate (FAR)) is calculated as follows: the first sample of each finger in the subset $A$ is matched against the first sample of the remaining fingers in $A$. If matching $g$ against $h$ is performed, the symmetric one (i.e., $h$ against $g$) is not executed to avoid correlation: ((100*99)/2) = 4,950. Therefore, it is possible to compute the False Rejection Rate (FRR), which is the likelihood of samples for the same finger being considered as having different fingers.

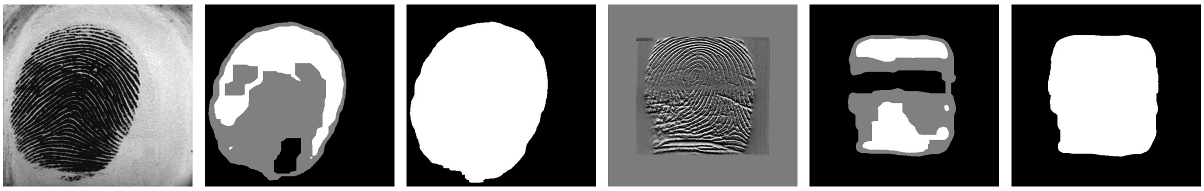
## 4.2 Griaule AFIS

In this study, Griaule AFIS Biometrics (2018) was used to represent and match fingerprints as minutiae. The Griaule fingerprint recognition framework won the Open Category, section "average results over all databases" of the Fingerprint Verification Contest 2006 (Cappelli et al., 2007), achieving the best average equal error rate (EER).

Minutiae matching is certainly the most well-known and widely used method for fingerprint correspondence, as an analogy with the way forensic experts compare fingerprint images and their acceptance as a proof of identity in court (Maltoni et al., 2009).

## 4.3 Quantitative Analysis

In this work, we used the DB2A and DB3A datasets in our experiments. Performance was measured through Equal Error Rate (EER) and Area Under the Recei-



(a) original (b) three regions (c) mask (d) original (e) three regions (f) mask

Figure 4: Fingerprint segmentation process: (a) original image; (b) three clustered regions by $k$-means; (c) image mask after watershed.

Table 1: Results of AUC and ERR metrics for fingerprint verification.

| | AUC | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2000 | | 2002 | | 2004 | | 2006 | |
| | DB2_A | DB3_A | DB2_A | DB3_A | DB2_A | DB3_A | DB2_A | DB3_A |
| Proposed OPS | 0.98886 | **0.95783** | 0.99467 | **0.97470** | 0.92707 | **0.96974** | **0.99751** | 0.97251 |
| Thai and Gottschlich (2016) | **0.98982** | 0.95679 | 0.99418 | 0.78710 | **0.95089** | 0.94713 | 0.99565 | 0.97158 |
| Kovesi (2018) | 0.96708 | 0.94134 | **0.99480** | 0.95188 | 0.95090 | 0.95118 | 0.98200 | **0.97315** |
| | EER | | | | | | | |
| | 2000 | | 2002 | | 2004 | | 2006 | |
| | DB2_A | DB3_A | DB2_A | DB3_A | DB2_A | DB3_A | DB2_A | DB3_A |
| Proposed OPS | **0.02524** | **0.07384** | 0.01279 | **0.05294** | 0.12369 | **0.05521** | **0.00857** | **0.04715** |
| Thai and Gottschlich (2016) | 0.02545 | 0.08116 | **0.00660** | 0.27725 | 0.09916 | 0.09359 | 0.01173 | 0.04904 |
| Kovesi (2018) | 0.04989 | 0.08209 | 0.01400 | 0.08138 | **0.09338** | 0.08236 | 0.03807 | 0.05826 |

ver Operating Characteristic Curve (ROC AUC) metrics (Toh et al., 2008; Vacca, 2007), considering the protocol proposed and used in the FVC.

A quantitative comparison of the results for EER and ROC AUC metrics for three segmentation methods applied to FVC datasets is shown in Table 1.

It can be observed that the proposed method achieved very competitive results, positioning slightly higher or below the other evaluated approaches, when AUC metric is considered. For EER metric, the proposed method obtained better rates than the other approaches.

## 4.4 Qualitative Analysis

Table 2 shows the segmentation results of some fingerprint images based on different techniques. The results indicate that the proposed segmentation method is highly competitive compared to the evaluated approaches.

Image segmentation is a challenging problem and many question remain open. Visual inspection conducted by experts is still important. Issues related to the size of the resulting segmented area, also known as regions of interest (ROI), may be relevant, in addition to aspects derived from the quantitative analysis.

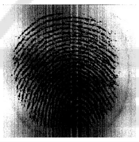
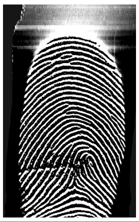
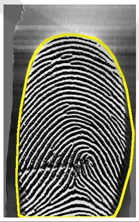
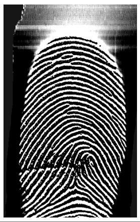
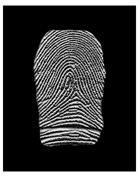
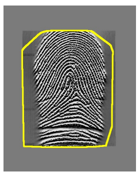
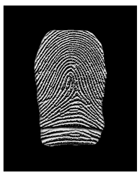
## 4.5 Discussion

Accurate segmentation is a complex, however, a critical task since it reduces the computational time of the following processing steps and discards spurious minutiae. Most of the segmentation methods available in the literature are highly dependent either on empirical thresholds or a well-trained model. Furthermore, many of these experiments are sensor dependent.

The proposed algorithm employs an unsupervised clustering based only on oriented features inherent to a fingerprint image. The parameter $k$, which refers to the number of regions to be created, can also be established from a preliminary evaluation of fingerprint quality, making this step more adaptive. The morphological watershed operation was applied to obtain two well-defined regions.

The fingerprint segmentation algorithm proposed in this work is suitable for different sensors and does not need empirical thresholds or a well-trained model. Experimental results using FVC2000, FVC2002, FVC2004 and FVC2006 datasets, showed that our approach, in addition to its computational simplicity, presents a lower classification error when compared to other segmentation methods.

Table 2: Comparative analysis among different fingerprint image segmentation methods.

| Dataset | Proposed OPS | Thai and Gottschlich (2016) | Kovesi (2018) |
| --- | --- | --- | --- |
| DB2A 2000 |  |  |  |
| DB3A 2000 |  |  |  |
| DB2A 2002 |  |  |  |
| DB3A 2002 |  |  |  |
| DB2A 2004 |  |  |  |
| DB3A 2004 |  |  |  |
| DB2A 2006 |  |  |  |
| DB3A 2006 |  |  |  |

# 5 CONCLUSIONS AND FUTURE WORK

This paper presented and evaluated a fingerprint image segmentation method. For each pixel, the algorithm calculates the dominant direction within a given neighborhood. By applying statistical measures, it is possible to compute the strength of anisotropic information. The proposed method also employed an unsupervised clustering algorithm to define the interest regions. Followed by a set of morphological operations, the fingerprint contour can be extracted.

The validity of the proposed method is demonstrated through a comparison against two other approaches available in the literature. No training or prior information about thresholding level is necessary, which makes the evaluation more independent. The proposed method is suitable for different sensors.

Directions for future work include the evaluation of the directional operator as a fingerprint image quality indicator. It could be integrated into a quality assessment framework along with other features. In addition, an accurate estimation of fingerprint orientation image is essential in fingerprint classification and this directional operator can also be used for this task.

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