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Latent Fingerprint Segmentation Using Modified ADTVM Model

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Abstract: ***Latent finger print identification has many roles in identifying and convicting criminals. Rolled and plain prints are obtained in an attended mode so that they are usually of good visual quality and contain sufficient information for reliable matching. On the other hand, latent prints are usually collected from crime scenes and often mixed with other components such as structured noise or other fingerprints. Existing fingerprint recognition algorithms fail to work properly on latent fingerprint images. Here we purpose a ADTV model for latent finger print segmentation. The proposed ADTV model decomposes a latent fingerprint image into two layers: cartoon and texture. The cartoon layer contains unwanted components (e.g., structured noise) while the texture layer mainly consists of the latent fingerprint. This cartoon-texture decomposition facilitates the process of segmentation, as the region of interest can be easily detected from the texture layer using traditional segmentation methods.***

Keywords: Fingerprint recognition, fingerprint segmentation, latent fingerprints, total variation.

1. Introduction

Fingerprint recognition or fingerprint authentication refers to the automated method of verifying a match between two human fingerprints. Fingerprints are one of many forms of biometrics used to identify an individual and verify their identity. Because of their uniqueness and consistency over time, fingerprints have been used for over a century, more recently becoming automated (i.e. a biometric) due to advancement in computing capabilities. Fingerprint identification is popular because of the inherent ease in acquisition, the numerous sources (ten fingers) available for collection, and their established use and collections by law enforcement and immigration.

1.1 What is a Fingerprint?

A fingerprint is the feature pattern of one finger (Figure 1.1). It is an impression of the friction ridges and furrows on all parts of a finger. These ridges and furrows present good similarities in each small local window, like parallelism and average width. Fingerprints are imprints formed by friction ridges of the skin and thumbs. They are used for identification because of their immutability and individuality. Immutability means that it is permanent and unchanging character of the pattern on each finger. And also it is individuality refers to the uniqueness of ridge details across individuals; the probability that two fingerprints are alike is about 1 in 1.9x1015.

However, manual fingerprint verification is so tedious, time consuming and expensive that is incapable of meeting today's increasing performance requirements. An automatic fingerprint identification system is widely adopted in many applications such as building or area security and ATM machines.

Figure 1.1: Fingerprint image from a sensor

However, shown by intensive research on fingerprint recognition, fingerprints are not distinguished by their ridges and furrows, but by features called Minutia, which are some abnormal points on the ridges (Figure 1.2). Among the variety of minutia types reported in literatures, two are mostly significant and in heavy usage:

- Ridge ending - the abrupt end of a ridge
- Ridge bifurcation - a single ridge that divides into two ridges

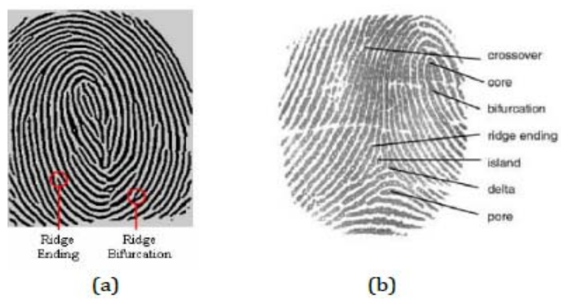

Figure 1.2(a) Two important minutia features

(b) Other minutiae features

The difficulty for latent fingerprint segmentation mainly lies in two aspects. First, the fingerprint is usually of very poor quality, often with smudged or blurred ridges. It is common that the image contains only a partial fingerprint region, and large nonlinear distortions exist due to pressure variations. As a result, while a typical rolled fingerprint has around 80 minutiae, a latent fingerprint contains only about 15 usable minutiae with reasonable quality. Second, the presence of various types of structured noise further hinders the proper segmentation for latent prints. As compared with the oscillatory ridge structures of fingerprints, structured noise is of much larger scale and can appear in various forms. Based on the appearance, structured noise can be classified into six categories: arch, line, character, speckle, stain and others.

1) **Arch:** The big arch is manually marked by crime-scene investigators to indicate the possible existence of latent fingerprints in the region encircled by the arch. The arch noise is viewed as the simplest type of structured noise.
2) **Line:** The line noise may appear in form of a single line or multiple parallel lines. A single line is often detected and removed using methods based on the Hough transform. Multiple parallel lines can be confused with fingerprints more easily since they share quite a few common features.
3) **Character:** This is one of the most common types of structured noise in latent fingerprints. Characters may appear in various font types, sizes and brightness. They can be either handwritten or typed.

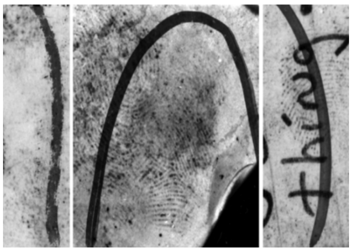

Figure 1.3: Arch

4) **Stain:** It is generated when the fingerprint was inadvertently smeared on a wet or dirty surface. Stain noise often appears in spongy shape with inhomogeneous brightness.
5) **Speckle:** As compared with lines and characters, speckle noise tends to contain tiny-scale structures, which are either regular (e.g., clusters of small dots) or random (e.g., ink and dust speckles).
6) **Others:** A latent fingerprint may contain other types of structured noise such as arrows, signs, etc. Being similar to arch noise and character noise, they usually consist of smooth surfaces with sharp edges.

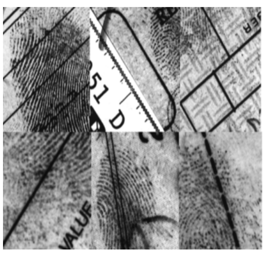


Figure 1.4: Line Figure 1.5: Character

For latent fingerprint segmentation, the main challenge lies in how to effectively separate latent fingerprints, the relatively weak signal, from all structured noise in the background, which is often the dominant image component. Additional complexity arises when structured noise overlaps with the fingerprint signal.

Previous methods proposed for fingerprint segmentation are mostly feature-based, and features commonly used for segmentation include the mean, variance, contrast, coherence as well as their variants. However, these methods may fail to work properly for latent fingerprints as they are based on many assumptions that are only valid for rolled/plain fingerprints. For instance, in, the mean feature was used since the background was assumed to be bright and the variance feature was used since the variance of background noise was assumed to be much lower than that in fingerprint regions. However, these assumptions are no longer valid in the context of latent fingerprint images.

2. Related Works

Total-Variation-based (TV-based) image models have been widely used in the context of image decomposition. Among several well known TV-based models, the model using total variation regularization with an L1 fidelity term, denoted by the TV-L1 model, is especially suitable for multiscale image decomposition and feature selection. A modified TV-L1 model was adopted in to extract small-scale facial features for facial recognition under varying illumination. More recently, the authors proposed an adaptive TV-L1 model for latent fingerprint segmentation in, where the fidelity weight coefficient is adaptively adjusted to the background noise level.

Furthermore, the Directional Total Variation (DTV) model was formulated in by imposing the directional information on the TV term, which proved to be effective for latent fingerprint detection and segmentation. It appears that the TV-based image model with proper adaptation offers a suitable tool for latent fingerprint segmentation. However, the performance of both models in was evaluated only subjectively, as no objective evaluation was performed to determine whether the proposed scheme improved matching accuracy, which is the ultimate goal for fingerprint segmentation.

The TV-L1 model with spatially invariant fidelity (1) does not generate the desired output throughout the entire fingerprint image. In the fingerprint region, when is well matched with the scale of fingerprints, all essential contents can be captured in texture layer. However, in the noisy region, some unwanted signals will be extracted to under the same value. In addition, being an isotropic model, the TV model minimizes the total variation of cartoon layer along all directions. This scheme does not fully exploit the orientation coherency, which is one of the most unique characteristics of fingerprints. These observations motivate us to study a more flexible image model that is capable of integrating the special characteristics of fingerprints.

It is called the Adaptive Directional Total-Variation (ADTV) model and formulated as

$$u^* = \operatorname*{argmin}_u \int |\nabla u \cdot \vec{a}(x)|\, dx + \frac{1}{2} \int \lambda(x)\, |u - f|\, dx,$$

In the early work of, segmentation was achieved by partitioning a fingerprint image into blocks, followed by block classification based on gradient and variance information. Where *f(x, y)* is the gray level value in the image at position (x, y)

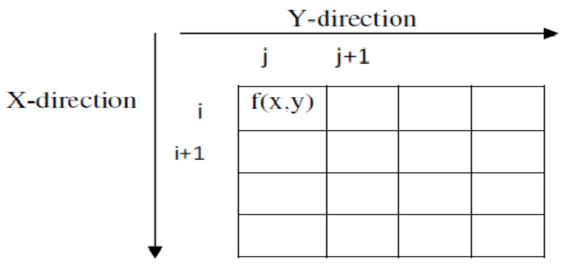

Figure 8: Image in X-Y direction

The *ROI* is the area of scanner surface that has been contacted with a finger surface and remain area is referred as background. The *ROI* includes all of information which is needed for fingerprint recognition. Also, the background doesn't have any useful information and is a noisy region. In order to analyze the fingerprint image, it is necessary the *ROI* to be segmented. The separation of *ROI* from the image background, where the background is removed from the processed image, is named as fingerprint segmentation

3. System Analysis

Many algorithms have been developed and all face nearly same problems. The background was not good distinguishable from the foreground. Chunxiao et al. Propose a hybrid algorithm based on block-wise classifier to separate the foreground from the background and pixel-wise classifier to deal with pixels accurately. Marques and Thome partitioned the image into various sub blocks, and then extract a feature vector based on its Fourier descriptors. Each one of these vectors is passed to a neural network that classifies it. In Ghassemian investigates a new on-line unsupervised ridges detection method that is based on fussy classification techniques. Chengpu et al. present a novel algorithm that firstly uses the method of gradient projection, secondly adopt gradient coherence and finally carry out morphological operation to get the exact foreground region. Zhu et al. propose a scheme for systematically estimating fingerprint ridge orientation and segmenting fingerprint image by evaluating the correctness of ridge orientation based on neural network. The neural network is used to learn the correctness of the estimated orientation by gradient-based method. Helfroush and Mohammadpour use a combination of three variance mean and ridge orientation features and also employs the median filter as a post processing step. Akram et al. present a modified gradient based method to extract region of interest. This method compute the local gradient values for fingerprint images which detect sharp change in the gray level value of background.

In, Bazen and Gerez propose also an algorithm that uses three pixel features, being the coherence, the mean and the variance. An optimal linear classifier is trained for the classification per pixel, while morphology is applied as post processing. Yin et al. show two steps for fingerprint segmentation to exclude the remaining ridge region from the background. The non-ridge regions and unrecoverable low quality ridge regions are removed as background in the first step, and then the foreground produced by the first step is further analyzed so as to remove the remaining ridge region. For latent fingerprint segmentation, the main challenge lies in how to effectively separate latent fingerprints, the relatively weak signal, from all structured noise in the background, which is often the dominant image component. Additional complexity arises when structured noise overlaps with the fingerprint signal. Previous methods proposed for fingerprint segmentation are mostly feature-based, and features commonly used for segmentation include the mean, variance, contrast, coherence as well as their variants. However, these methods may fail to work properly for latent fingerprints as they are based on many assumptions that are only valid for rolled/plain fingerprints. For instance, in, the mean feature was used since the background was assumed to be bright and the variance feature was used since the variance of background noise was assumed to be much lower than that in fingerprint regions. However, these assumptions are no longer valid in the context of latent fingerprint images.

3.2 Proposed System

The TV-L1 model with spatially invariant fidelity does not generate the desired output throughout the entire fingerprint image. In the fingerprint region, when is well matched with the scale of fingerprints, all essential contents can be captured in texture layer. However, in the noisy region, some unwanted signals will be extracted to under the same value. In addition, being an isotropic model, the TV model minimizes the total variation of cartoon layer along all directions. This scheme does not fully exploit the orientation coherency, which is one of the most unique characteristics of fingerprints. These observations motivate us to study a more flexible image model that is capable of integrating the special characteristics of fingerprints. It is called the Adaptive Directional Total-Variation (ADTV) model and formulated as

$$u^* = \operatorname*{argmin}_u \int |\nabla u \cdot \vec{a}(x)|\, dx + \frac{1}{2} \int \lambda(x)\, |u - f|\, dx,$$

Where a (x) spatially varying orientation vector is adjusted by the local texture orientation, and is spatially varying parameters that control the feature scale.

The spatially varying parameter, $\lambda(x)$, can be understood in two ways. First, is a scalar that controls the scale of features appearing in at pixel? A large value enforces most textures to be kept in, leaving only tiny-scale structures in. When is sufficiently large, and the original content is almost totally blocked from. Thus, second, parameter can be interpreted as a weighting coefficient that balances the importance between fidelity and smoothness. In the fingerprint region, the value should be relatively small since low fidelity ensures the smoothness of and, thus, more textures will go to. In regions with structured noise, fidelity becomes important and a large value ensures all noise components to be filtered out from texture.

Algorithm 1. Augmented Lagrangian method for our proposed ADTV model.

1) *Initialization:* $u^0 = 0, \vec{p}^0 = 0, q^0 = 0, w^0 = 0$;
2) For $k = 0, 1, 2, \ldots$, compute:

$$(u^{k+1}, \vec{p}^{k+1}, q^{k+1}, w^{k+1}) = \underset{(u,\vec{p},q,w)}{\operatorname{argmin}} \mathfrak{L}(u, \vec{p}, q, w, \vec{\mu_p}^k, \mu_q^k, \mu_w^k). \quad (4)$$

3) *Update:*

$$\vec{\mu_p}^{k+1} = \vec{\mu_p}^k + r_p(\vec{p}^{k+1} - \nabla u^{k+1})$$
$$\mu_q^{k+1} = \mu_q^k + r_q(q^{k+1} - \vec{p}^{k+1} \cdot \vec{a})$$
$$\mu_w^{k+1} = \mu_w^k + r_w(w^{k+1} - u^{k+1}).$$

4. Implementation

4.1 Orientation Estimation

For extract the fingerprint components to texture output, it should be spatially varying and well aligned with the local fingerprint ridge orientation. here the gradient-based approach is used to compute the coarse orientation field at each pixel:

$$o(x) = \frac{1}{2}\tan^{-1}\frac{\sum_W 2f_{x_1}f_{x_2}}{\sum_W(f_{x_1}^2 - f_{x_2}^2)} + \frac{\pi}{2},$$

Where W is a neighborhood window around, a(x) is the radiant vector at x(f_{x1},f_{x2}) , and is a 4-quadrant arc tangent function with output range of(-Π,Π) . This estimation given above is relatively accurate only at fingerprint regions, while it becomes less reliable at noisy regions. Thus the reliability of the orientation field by its local coherency:

$$c(x) = \frac{(\sum_W(f_{x_1}^2 - f_{x_2}^2))^2 + 4(\sum_W f_{x_1}f_{x_2})^2}{(\sum_W(f_{x_1}^2 + f_{x_2}^2))^2},$$

a) Scale Parameter Selection:
By applying one uniform value over the entire fingerprint image does not generate satisfactory results. To improve the result, the value $\lambda(x)$ of should be spatially adaptive. That is, ought to be adaptively chosen according to the background noise level. Ideally, parameter should be larger in regions with higher structured noise and smaller in fingerprint regions. To differentiate these regions, we study their characteristics after going through local low-pass filtering. When an input image, is locally filtered by a low-pass filter denoted by

$$L_\sigma(\xi) = \frac{1}{1 + (2\pi\sigma|\xi|)^4},$$

b) Region-of-Interest Segmentation and Enhancement:
After decomposing the latent fingerprint image using the proposed ADTV model, we obtain two image layers: 1) cartoon, which contains the majority of unwanted content (e.g., structured noise, small-scale structures), and 2) texture, which consists of latent fingerprints and only a small amount of random noise. This decomposition facilitates two procedures: segmentation and enhancement. The variance value acts as a key segmentation feature for rolled/plain fingerprints this feature cannot be directly applied to latent fingerprints due to the presence of structured noise. However, after the cartoon-texture layer decomposition, most high-variance noise components are kept away from texture layer, allowing us to use the variance features for segmentation. Foreground/background regions are more widely separated after the ADTV-based decomposition, making it possible to conduct segmentation by simple variance based block classification. In addition, the proposed decomposition scheme is capable of enhancing the fingerprint quality. After decomposition, we remove all unwanted components that may overlap with fingerprints in texture layer. The extracted patterns are less degraded by structured noise and free from the illumination effect, leading to enhanced fingerprint quality.

The segmentation of latent finger print can be divided into a no of modules,

4.1 Sensing and Image Acquisition

The acquisition of a fingerprint images was accomplished by using off scan. Off-line sensing is defined as ink then his finger is pressed in a paper produce the digital image. This type of scanning is common in crime scene to obtain a latent fingerprint. However, live-scan scanners become presently more frequent, because of its simplicity in usage. There is no need for ink. The digital image is directly acquired by pressing against the surface of the scanner. The development of live disadvantages including:

- The difficulty of managing wet and dry fingers
- The misrepresentation slightly against the surface of the scanner
- The inability to detect false finger.

Both techniques are involved by some factors that make. Therefore the quality of a fingerprint scanner, the acquired image can extremely affect the performance of a fingerprint recognition algorithm. Off-line sensing or live ink-technique. An individual place his finger in black ink card.

4.2 Pre-Processing

To simplify the task of minutiae extraction and make it more easy and reliable, some preprocessing techniques are applied to the raw input image. Enhancement and segmentation of the fingerprint are the most commonly methods performed in the preprocessing step. The principal aim of enhancement is to improve the clarity of ridge in the recoverable area in the image and to assign the unrecoverable ridges as a noisy area. Recoverable region is considered when ridges and valleys are corrupted by a small amount of dirt, ceases, or other kind of noise. Unrecoverable region are the regions which are impossible to recover them from a very corrupted and noisy image. The most famously enhancement technique is contextual filter. This filter depends on changing filter parameter in relation to the local characteristic of the image. This parameter can be local ridge orientation or local ridge frequency.

However the primary purpose of segmentation is to avoid extraction of feature in the background that is in reality considered as a noisy area. Segmentation indicates the separation of fingerprint area or foreground from the image background. Due to the streaked nature of the fingerprint area, a simple thresholding technique is not sufficient. In addition to the presence of noise in a fingerprint image, fingerprint segmentation requires more robust and strong techniques.

4.3 Feature Extraction

After preprocessing step, the segmented and enhanced fingerprint is further processed to identify the main and distinctive minutiae. Most of the minutiae extraction methods necessitate the fingerprint gray-scale image to be transformed into a binary image. The acquired binary image is forwarded to a thinning stage to reduce the thickness of the ridge to one pixel ridge. Afterwards, the minutiae are simply detected by a simple image scan. Due to the characteristic of the pixel that corresponds to minutiae, the simple scan image is one of many methods developed for minutiae detection. It depends on calculating crossing number of a pixel. The crossing number is the half sum of the differences between pairs of adjacent pixels in the 8-neighborhood of p. Since the minutiae pixel can be bifurcation, crossover, termination, and so on. Therefore, the crossing number for minutiae must be different from 2.

To avoid the problems related to fingerprint binarization and thinning, many methods have been proposed. Direct gray-scale minutiae extraction is one of these methods. The basic idea of this algorithm is to track the ridge lines in the gray-scale image by going according to the local orientation of the ridge. When a ridge line terminates or intersects another line, the algorithm detects this location as a minutiae point.

4.4 Normalization

Let I(i,j) denotes the gray level value at pixel (i,j) M and VAR denote the estimated mean and variance of I respectively and G(I,j) denote the normalized gray level value at pixel (i,j) .the normalized image is defined as follows:

$$\mathcal{G}(i,j)=\begin{cases} M_0+\sqrt{\frac{VAR_0(\mathcal{I}(i,j)-M)^2}{VAR}}, & \text{if } \mathcal{I}(i,j)>M \\ M_0-\sqrt{\frac{VAR_0(\mathcal{I}(i,j)-M)^2}{VAR}}, & \text{otherwise,} \end{cases}$$

Where M_0 and VAR_0 are the desired mean and variance values respectively. Normalization is a pixel wise operation. It does not change the clarity of the ridge and furrow structures. The main purpose of normalization is to reduce the variations in gray level values along ridges and furrows.

4.5 Orientation Image

The orientation image represents an intrinsic property of finger print images and defines invariant coordinates for ridges and furrows in a local neighborhood. By viewing a finger print image as an oriented texture, a number of methods used here we use an gradient based approach as follows:

$$o(x)=\frac{1}{2}\tan^{-1}\frac{\sum_W 2f_{x_1}f_{x_2}}{\sum_W(f_{x_1}^2-f_{x_2}^2)}+\frac{\pi}{2},$$

4.6 Matching

Algorithms that extract important and efficient minutiae, will improve the performance of the fingerprint matching techniques. The features extracted of the input image are compared to one or more template that was previously stored in the system database. Therefore the system returns either a degree of similarity in case of identification or a binary decision in case of verification. Due to many factors that affect the variability of fingerprint image of the same finger, matching techniques get to be a hard problem. Some of these factors are mentioned below:

- Fingerprint pressure, dryness, sweat, dirt, humidity
- Placement of the finger in different locations on the sensor

Rotation of the finger at different angles to the sensor
Residues from the previous fingerprint acquisition
Feature extraction errors

Minutiae-based and correlation-based matching techniques are the most common techniques in fingerprint matching. In Minutiae-based techniques, first systems extract the minutiae in both images then the decision is based on the correspondence of the two sets of minutiae locations. However in correlation-based techniques compare two fingerprints based on their gray level intensities. First it selects relevant templates in the primary fingerprint then it uses template matching to locate them in the secondary image and compare positions of both fingerprints.

5. Conclusion and Future Work

While current automated a fingerprint identification system have achieved high accuracy in matching rolled/plain prints, latent fingerprint matching remains to be a challenging problem and requires much human intervention. The goal of this work is to achieve accurate latent segmentation, which is an essential step towards automatic latent identification. Existing fingerprint segmentation algorithms perform poorly on latent fingerprints, as they are mostly based on assumptions that are only applicable for rolled/plain fingerprints.

In this work, we proposed the Adaptive Directional Total Variation (ADTV) model as an image decomposition scheme that facilitates effective latent fingerprint segmentation and enhancement. Based on the classical Total-Variation model, the proposed ADTV model differentiates itself by integrating two unique features of fingerprints, scale and orientation, into the model formulation. The proposed model has the ability to decompose a single latent image into two layers and locate the essential latent area for feature matching. The proposed ADTV scheme can be viewed as a preprocessing technique in automatic latent fingerprint recognition. It also has a strong potential to be applied to other applications, especially for processing images with oriented textures. This study can be further extended along the following directions:

1) The effectiveness of the proposed scheme is related to the accuracy of orientation estimation. When the estimated orientation is unreliable, fingerprint patterns may not be fully extracted to texture layer, leading to poor segmentation and enhancement results. In addition, the positions of singular points were not taken into consideration by the proposed model. Additional detection and processing techniques can be introduced for handling regions surrounding the singular points.
2) Some structured noise may have very similar characteristics as fingerprint patterns and cannot be blocked from the texture layer. For example, parallel straight lines have high coherency similar to fingerprints and could be extracted to the texture layer as well. Adding a preprocessing step to remove this type of structure noise may be a possible solution.
3) The proposed ADTV method is incapable of handling regions with overlapped fingerprints, as our model formulation is designed to identify regions with coherent orientations along one single direction. To handle images with overlapped fingerprints, some sophisticated local analysis has to be conducted and integrated into the model formulation.

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