Improved Fingercode Alignment for Accurate and Compact Fingerprint Recognition

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***Abstract*—The traditional texture-based fingerprint recognition system known as FingerCode is improved in this work. Texture-based fingerprint recognition methods are generally more accurate than other methods, but at the disadvantage of increased storage requirements. The low storage requirements for a low resolution texture-based fingerprint recognition method known as FingerCode enables the combined use of fingerprints with the additional security of other devices such as smartcards. The low recognition accuracy of FingerCode is addressed using a novel texture alignment technique. As a result, an improved recognition accuracy is achieved without increasing storage requirements.**

***Index Terms*—alignment, FingerCode, fingerprint, texture-based,**

I. Introduction

Passwords and access cards have been traditionally used to restrict access to secure systems or locations. However, their widespread use have introduced security risks such as stolen passwords and access cards. This resulted in the emergence of biometrics, which addressed these security risks up to a certain degree. Biometrics are used as an automated process of recognizing an individual based on their physical or behavioral characteristics. Later, devices such as access cards evolved into smart cards, which contain a limited amount of storage capacity. This enabled the combination of biometrics with these smart devices. The fingerprint in particular showed promise with the breakthrough of a texture-based fingerprint recognition method known as FingerCode by Jain *et al.* [1].

The texture pattern of a fingerprint is known to contain richer information than singular points and minutiae [2]. However, the detailed texture patterns are often too large to store on compact devices such as smartcards without lower the resolution substantially as in the case of FingerCode. Texture-based features, also known as global features, consist of the ridge texture pattern, orientation and frequency. Minutiae-based features, also known as local features, contain less information than the texture pattern, but are very storage efficient. However, local features are often distorted in bad quality fingerprint images, resulting in incorrectly detected features.

Hybridization of texture-based and minutiae-based features is an efficient way to improve fingerprint matching performance [3]. Jain *et al.* [4] proposed a hybrid system that summarizes texture-based information as macro features and combines the result with a minutiae-based approach for an improved FingerCode recognition performance. The macro features are determined by a circular tessellation mask on filtered images centred at a reference point. The minutia points are used to align the database and test fingerprints. This fingerprint recognition algorithm is known as the hybrid FingerCode method and is more robust to low quality input data than the traditional FingerCode algorithm. Additional FingerCode templates are created by rotating up to 45° in both directions to handle unaligned images. They show that the alignment problem is a critical factor to consider for a high recognition accuracy and to avoid system failure. However, they do not address this problem in a reliable way.

Manipulation of minutiae and singular points are considered as a comprehensive alignment technique for the FingerCode algorithm. The minutiae features are used as a reference alignment system for an improved FingerCode algorithm. The alignment process is extended to include affine transformation for more accurate alignment of texture. This approach will be compared with the FingerCode method described in [4].

The rest of the paper is organized as follows: Section II presents the related studies. Section III discusses the construction of the improved hybrid FingerCode system. The experimental analysis and results are discussed in Section IV. Section V concludes the paper.

II. Related Studies

FingerCode [1] uses circular tessellation of filtered fingerprint images centered at the reference point, which results in a circular ROI generally containing 80 sectors. The ROI is further processed to generate eight-dimensional features maps by computing their average absolute deviation (AAD) features. Multiple FingerCode templates are created by rotating the resulting ROI by up to 45° in both directions to handle unaligned images. The matching performance of this method is directly proportional to the accurate determination of the reference point, which is based on the quality of the fingerprint images. Moreover, this FingerCode method cannot guarantee that a reference point will be found on every type of fingerprint image such as the arch-type and for the poor quality fingerprint images.

Many improved fingerprint alignment and reference point detection methods have been studied. The new approach by Jain *et al.* [4] performed the best by using a fingerprint alignment technique that exploits the spatial coordinates of the reference minutia pair, also known as the hybrid FingerCode method. Other methods such as Chan *et al.*'s approach [5] used a rotation-invariant reference point location in combination with orientation features to improve the reference point detection performance. Fingerprint texture alignment is still a problem because the preceding approaches and many others do not sufficiently enhance the image in the pre-alignment stage and do not have a fall-back mechanism stage in case reference point detection fails. Since then, FingerCode has become a lesser studied problem and limited research is available. Fingerprint texture alignment is thus a non-trivial task and requires a new approach as a bid to improve FingerCode recognition performance.

III. Methodology

This section describes the image processing techniques used to develop the proposed hybrid FingerCode algorithm.

A. Orientation Map

Turonni *et al.* compare several orientation estimation algorithms and show that reliable orientation extraction in low-quality fingerprint regions is still a problem [6]. However, they show that applying denoising algorithms during pre-processing and block averaging techniques during post-processing significantly improve orientation estimation. The orientation map is a key step for accurate reference point detection, thus a reliable ridge enhancement algorithm is necessary.

Buades *et al.* [7] created an image denoising algorithm, called non-local means filtering (NL-means), described as neither local nor global. NL-means differs from typical neighbourhood filters as it compares the geometrical configuration in an entire neighborhood instead of a single greyscale pixel of one neighbourhood corresponding to another thus preserving the edges of an image, but also smoothing some of the detail. The NL-means filter is thus combined with an inverted Gaussian filter to denoise the image followed by enhancing the fingerprint ridges before calculating the orientation map.

B. Reference Point Detection

At global level, there are unique points on the fingerprint located on ridge curvatures that are sharper or unique to other areas. They are commonly known as singular points and generally refer to a core point and one or more delta points. The core point, also known as the reference point, is often defined as the sharpest concave ridge curvature [4]. It is especially useful as it serves as a guide during image registration and segmentation.

The Poincaré index is determined based on the orientation map [4]. This method works well in good quality fingerprint images, but fails to correctly localize reference points in poor quality fingerprints with cracks, scars or poor ridge and valley contrast. Utilizing the NL-means filter before calculating the orientation map sufficiently improves most poor quality fingerprints for reliable core detection. However, in this paper a fall-back mechanism is implemented to prevent system failure in the rare case that this enhanced Poincaré index approach fails.

The fall-back mechanism uses the local binary patterns histogram (LBPH) feature descriptor as a confidence score for reference point detection. LBPH uses a special local binary pattern (LBP) operator known as extended LBP (ELBP). The neighbourhood is extended to include interpolated pixels, based on a circular mask, capturing finer grain texture. This fall-back mechanism precisely provides the best case reference point given a trained image and test image.

C. Image Segmentation

A fingerprint image has a region of interest (ROI), containing ridges and valleys, known as the foreground. A circular 80 pixel radius ROI is cropped around the core point. The rest of the image processing is applied on the ROI to reduce computation time and noise.

D. Gabor Filter

Feature extraction is performed by the convolution of a Gabor filter bank with orientations corresponding to the texture of the image. These local orientations are extracted from the orientation map. Eight orientations are used to describe both local and global features.

E. Ridge Thinning

Ridge thinning is used to eliminate the redundant pixels of ridges. Fingerprint thinning algorithms should preserve the topology of the ridges and connectivity. The thinning should be applied to a binarized fingerprint image by thinning certain pattern shapes until it is represented by 1-pixel wide lines, using morphological operations [8].

The modified Zhang-Suen thinning was implemented after considering multiple thinning algorithms [8].

F. Minutiae Detection

Minutiae extraction and labelling is the next important step after ridge thinning. Minutiae extraction can be performed using the crossing number method and typically uses a 3×3 pixel sliding window [9]. This effectively creates an eight-directional minutiae mask.

After the fingerprint ridge thinning, marking minutia points is the next important step. False minutiae are reduced by considering ridge endings and bifurcations as a single type.

Fig. 1: Unaligned Test Image.

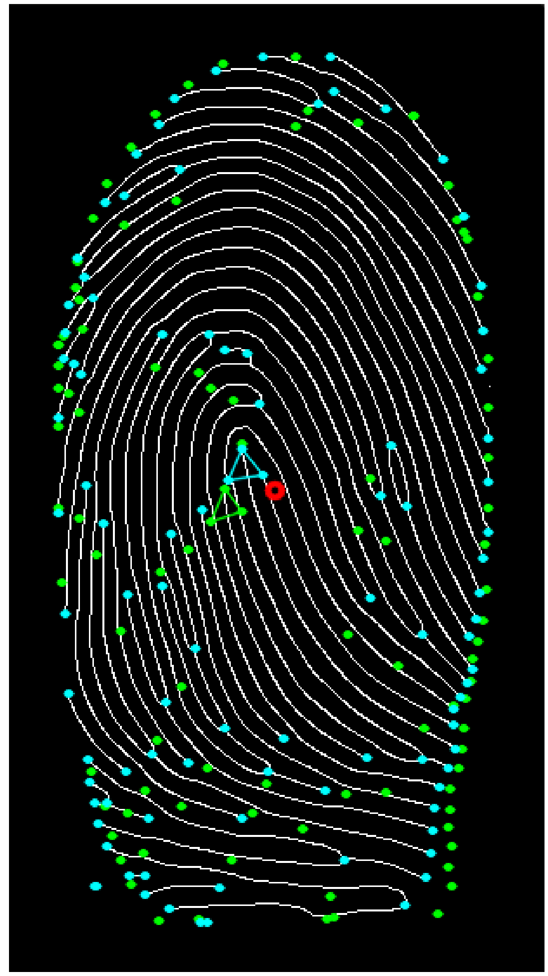

Fig. 2: Initial Stage of Aligning the Test Image using Minutiae Triplets of the Corresponding Database Image.

G. Novel Alignment Algorithm

Minutiae triplets or triangles are formed using three minutiae. It provides more discriminative information than a single minutia point correlation and reduces deformation effects due to skin elasticity and inconsistent contact pressure during fingerprint acquisition. Triangle side length constraints are used to guarantee a constant number of triplets. Remaining false minutiae are catered for using an appropriate binning mechanism based on the shortest Euclidean distance among stored triplet points [2].

The test image that requires alignment is shown in Fig 1. Triplets of both the test and database image are aligned relative to the reference point. Fig 2 shows the test skeleton image with the green minutiae, corresponding to the database image, and the blue minutiae, corresponding to the test image, which is represented by the skeleton image in the figure. The red point signifies the reference point of the database image. This initial minutiae triplet alignment serves as a foundation for the following alignment process. The initially aligned test image and database image are illustrated on the left and right of Fig 3, respectively.

The novelty of the proposed system lies in the combination of the initial minutiae triplet alignment with the affine transformation based on the calculation of the enhanced correlation coefficient (ECC) [10]. This method attempts to warp the initially aligned texture of a test image according to the trained image in the database. The confidence score is once again determined by the LBPH method. This is also used as a pre-classifier before FingerCode extraction and matching. The final aligned test image and database image are illustrated on the left and right of Fig 4, respectively.

H. FingerCode Extraction

The FingerCode feature vector is determined as follows.

1) The ROI is tessellated into six concentric circles divided into 16 sectors. Grey-level normalization is performed on individual sectors rather than the entire image in order to capture the intensity variations in different parts of the image.
2) The AAD is computed from the mean of grey values in individual sectors of filtered images to define the feature vector. AAD features give slightly better performance

Fig. 3: Initial Alignment of Test Image vs. Corresponding Database Image.

Fig. 4: Novel Alignment of Test Image vs. Corresponding Database Image.

than variance features and are therefore used. Each of the 80 sectors are Gabor filtered at eight directions, thus totaling 640 features per fingerprint, which are stored as a compact FingerCode.

Referring to Fig 5, the first four FingerCodes and their corresponding AAD images are at the bottom and top, respectively.

IV. Experimental Analysis and Results

A total of 48 fingerprint images are used for this experiment. The images were obtained from the BioSecure sample multimodal database, consisting of the thumb, index and middle fingers of one male and one female. The database FingerCodes were trained on 6 of the total images. The remaining 42 were used as the test set.

The accuracy of this FingerCode biometric system, given in Figure 6, is illustrated as a Receiver Operating Characteristic (ROC) curve showing the relationship between the Genuine Accept Rate (GAR) and the False Accept Rate (FAR) at different Euclidean distance thresholds.

The proposed FingerCode approach achieves a 100% GAR at an 5.56% lower FAR and a 0% FAR with an improved GAR of 8,33% over the hybrid FingerCode system. The results show that the proposed fingerprint recognition system can be a good initial fusing candidate in a multi-modal biometric system.

V. Conclusion

Texture-based features contain richer information than minutiae-based features, but require a lot of storage capacity. The traditional FingerCode algorithm showed promise with low storage requirements, but reduced the recognition accuracy potential of high resolution texture-based methods. Hybrid FingerCode improved the recognition accuracy to acceptable levels. This paper proposed an improved hybrid FingerCode system with the same low storage requirements, but achieved a significantly higher accuracy than the original hybrid FingerCode. Furthermore, our system is not susceptible to the accuracy loss caused by low quality input data resulting in system failure during reference point detection. The proposed hybrid FingerCode system thus achieved a higher accuracy than the hybrid FingerCode method by eliminating system failure. This was also attributed to a novel texture alignment algorithm that used minutiae triangles and affine transformations based on ECC with a fall-back mechanism in the rare case of system failure. The initial results of this alignment algorithm are promising as it offers a reliable solution to the texture alignment problem on the well-studied FingerCode system.

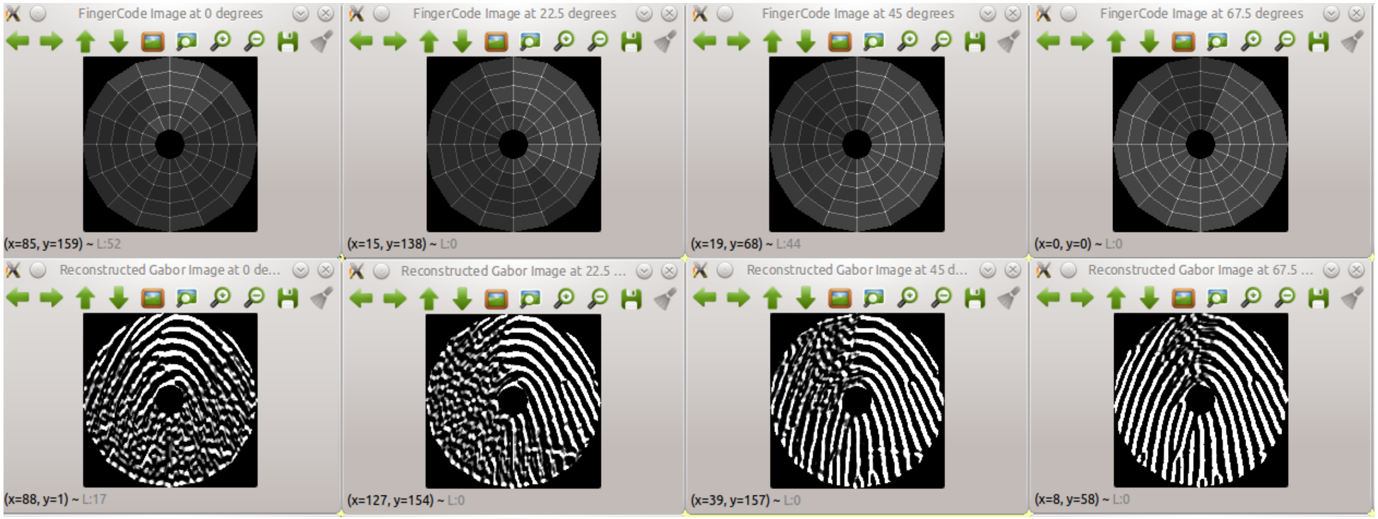

Fig. 5: Four FingerCodes and their corresponding AAD images.

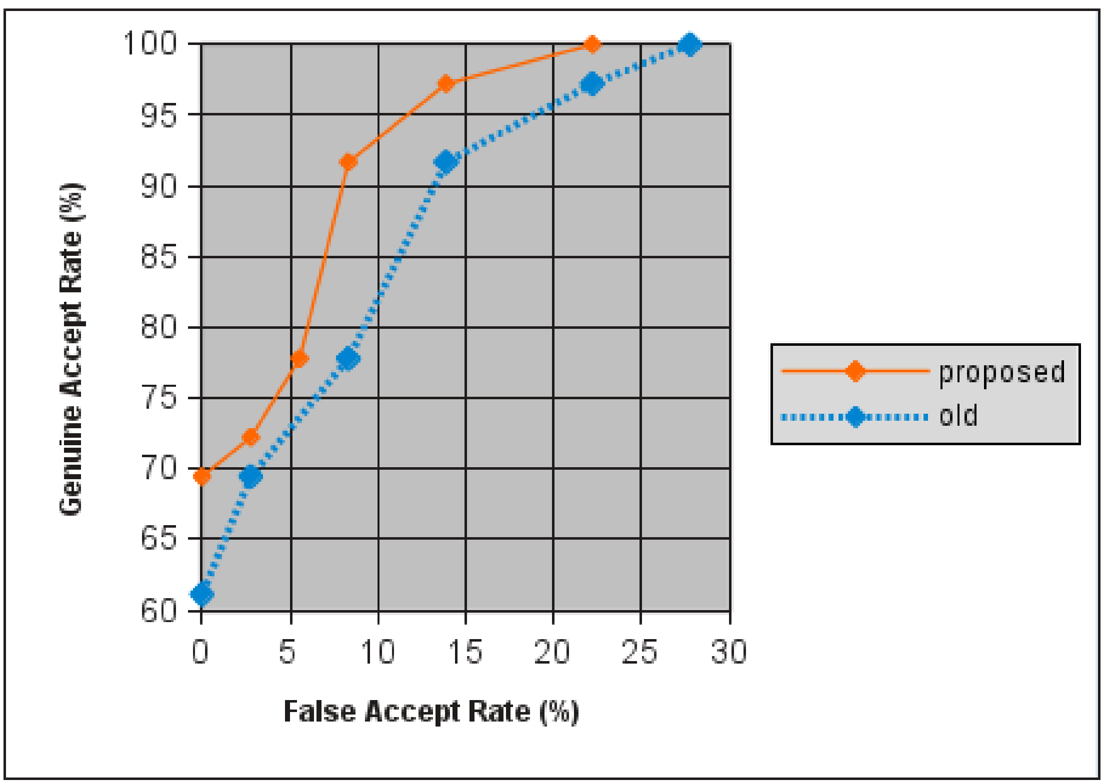

Fig. 6: The ROC curve comparing the accuracy of the old filter-based FingerCode approach to the proposed approach

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