A new biometric system based on inner-knuckle-print recognition

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Abstract. Biometrics is a highly efficient method of personal identification in civil fields. In this paper, we present a new biometrics system based on inner-knuckle-print (IKP). A new IKP image acquisition device with a finger guide is built for restricting the finger posture in a friendly way. A modified maximum curvature point method is proposed for feature extraction; it can extract the central region of the IKP line pattern robustly against illumination variation. The experimental results show that the proposed method achieves the equal error rate of 0.36%, performing better other traditional methods. In addition, it works in real-time.

1. Introduction

In recent years, the pattern of the inner-knuckle-print (IKP) has been found to be unique, which implies that it can be used for personal authentication [1]. Compared with other biometrics systems, such as face, fingerprint, and iris, the IKP recognition system has several advantages. First, the line pattern of the knuckle is clear and stable, and it contains rich unique information. It is also easy to capture with a cheap CCD or CMOS camera. Moreover, the IKP recognition system can be combined easily with other biometrics system, such as finger print, finger vein, or palm print for achieving a more accurate and robust system. Therefore, the IKP recognition system has attracted a lot of attention, and some progress have been made.

Li et al. proposed to extract four IKP ROIs and palm print ROI simultaneously from the image of the entire hand, then identified the person based on the fusion score [1]. Liu et al. applied an improved local binary pattern (LBP) to extract local IKP feature [2]. And a cross-correlation-based algorithm was used for feature matching. In addition, they developed another IKP feature extraction method based on the combination of Gabor filtering and derivative line detection [3]. Score level fusion of the middle and ring fingers was investigated, too. To achieve deformation tolerance, Xu et al. represented the feature map with the magnitude of the CompCode, then encoded it into a feature vector based on a new structure-context descriptor [4]. And the similarity of the feature vector was measured by the earth mover distance. Some key-point matching methods, like ORB [5], were also reported. In addition, some studies have been conducted on the multi-modal recognition system by combining IKP with other biometrics features [1, 5-9].

However, some important issues still exist. First, most IKP images suffer from more or less finger deformation, which degrades the recognition accuracy and is difficult to eliminate by image processing.
Thus, it is crucial to restrict the finger posture for a robust system when capturing the IKP image. Second, since the IKP pattern is usually composed of several line segments with few intersections, traditional key-point matching methods, such as SIFT, SURF and ORB [5], can hardly extract sufficient reliable key-points for feature matching. Thus, many researchers chose the template-matching methods, like CompCode [10], RLOC [11], and LBP [2]. Specifically, the CompCode and RLOC calculate the feature map by finding the dominant direction of line pattern. However, they are not very reliable in the smooth area and are easily affected by the uneven illumination. The LBP feature, which represents the relative brightness distribution of the neighboring pixels, is highly sensitive to random noise. Therefore, we still lack a robust method for IKP extraction.

To solve this problem, we propose a modified maximum curvature point method, namely MMCP, which can extract the central region of the IKP line pattern robustly against illumination variation and random noise. In addition, to evaluate the accuracy of the method, an IKP image database is established, which contains 1987 different images in 209 classes. The experimental results show that the proposed method achieves an equal error rate (EER) of 0.36%, which is considerably better than other traditional methods. Moreover, the average time cost for feature matching is only 3.48 ms, meaning that the system can work in real-time even if the database contains hundreds of samples.

The rest of the paper is organized as follows: Section 2 introduces the IKP recognition system; Section 3 presents the IKP feature extraction and matching method; Section 4 reports the experimental results; Section 5 represents the concluding remarks.

2. IKP recognition system

![Figure 1. Schematic diagram of the proposed IKP-based personal authentication system.](image)

Fig. 1 shows a schematic diagram of the IKP-based recognition system, which consists of an IKP acquisition device and an image processing module. The IKP acquisition device is shown in Fig. 2(a), whose overall size is $55 \times 38 \times 40$ mm. It is composed of a VGA camera, some fill-in light LED at wavelength of 468 nm, and a USB control board. All of the components are fixed in a box. The user only needs to put a finger on the finger guide, which is an indentation on the box, to capture the IKP.
image, as shown in Fig. 2(b). Examples of IKP images captured from different fingers are shown in Fig. 3. The size of the image is 448 × 292 pixels at resolution of 306 DPI. Since it is not necessary to use such a high resolution in our system, the image will be down-sampled to approximately 150 DPI. After this, the IKP sub-image is cropped from the original image and the feature pattern is then extracted. Finally, the feature map is added to the database for registration or compared with the feature template from the database for a matching score.

3. Feature extraction and matching

3.1. ROI extraction
In our system, we employ the IKP pattern from the middle node of the finger for recognition; this usually contains richer line pattern information and less deformation. First, we extract the contour of the finger automatically using a Sobel operator. Then, the rotation of the finger is estimated based on the finger contour, followed by the rotation correction operation. Finally, the IKP ROI is located using Radon projection, which covers the most informative areas in the projected result with a predefined length. As a result, all of the IKP ROI images are normalized to the same scale, rotation and translation, with a fixed size of 146 × 70 pixels. An example of the ROI extraction process is shown in Fig. 4.
3.2. Image pre-processing

On the basis of ROI extraction, we apply a 2D symmetric Gaussian filter with standard deviation of 1.3 to smooth the noisy image. Then, we normalize the brightness of the image using Eq. (1):

$$\hat{I}(x, y) = \hat{\mu} + \frac{\hat{\sigma}}{\sigma}(I(x, y) - \mu)$$

Where $I(x, y)$, $\mu$ and $\sigma$ are the brightness, mean, and deviation of the image before normalization, respectively; and $\hat{I}(x, y)$, $\hat{\mu}$, and $\hat{\sigma}$ are the corresponding brightness, mean and deviation of the image after normalization, respectively. Therefore, the processed images have similar mean and deviation values.

3.3. IKP feature extraction

The maximum curvature point (MCP) algorithm [12], which is widely used in finger vein extraction field, can extract the centerline of the vein pattern robustly against brightness and width. Considering that both of the vein and IKP are dark line pattern in the finger image, the MCP method should also be suitable for IKP extraction. However, since the image is the 2D discreet signal in pixels, the position of the centerline is easily affected by the quantization error, and varies over a small range. In addition, factors such as finger posture, image blur, and random noise also lead to the shift of the centerline, causing similarity degradation. Thus, we propose a modified maximum curvature point (MMCP) algorithm, which can extract the central region of the IKP pattern, instead of the single line. And it is more tolerable of the shift of the centerline. Here follows the details.

3.3.1. Calculation of the curvature of the image profile. The line pattern of IKP is always darker than the surrounding area, which results in a concave curve on the cross-sectional profile of the image. In addition, the center point of the line pattern usually has local maximum curvature, which make it easily distinguishable from the background. An example is shown in Fig. 5.
Figure 5. (a) Input image. (b) Cross-sectional profile of the corresponding line. (c) Curvature of the cross-sectional profile.

The curvature $\kappa_\theta(z)$ can be calculated by Eq. (2):

$$\kappa_\theta(z) = \frac{d^2 P_\theta(z)}{dz^2} \left\{1 + \left[ dP_\theta(z)/dz \right]^2 \right\}^{3/2}$$  \hspace{1cm} (2)

Where $P_\theta(z)$ is a cross-sectional profile in direction $\theta$, and $z$ is the position in the cross-sectional profile. Fig. 5(c) shows the $\kappa_\theta(z)$ distribution at the middle of the image where $\theta$ is zero.

After the curvature of the profile is calculated, we check each pixel in the profile until we locate all those points with local maximum curvature, which indicates the center positions of the IKP line pattern. The positions of these points are defined as $z_i$, where $i = 0, 1, \ldots, N - 1$, and $N$ is the number of local maximum points in the profile. For each $z_i$, the central area is defined as \{ $z | z \geq z_i - 1$ and $z \leq z_i + 1$ \}. This means every IKP line is represented by a fixed in width of three pixels. Pixels located in the central region are labelled with their curvature values in the feature map, and others are labeled as zero.

After all of the profile in direction $\theta$ have been searched and labeled, a curvature map $V_\theta(x,y)$ can be obtained, which indicates the possible IKP patterns spreading in this direction.

3.3.2. Search for IKP pattern in all direction. The profile in all directions are searched to obtain the IKP patterns spreading in all directions. In fact, only four directions need to be searched for computation efficiency, namely $\{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$. Then, we obtain the feature map using Eq. (3):

$$V(x,y) = \max \{V_0(x,y), V_{45}(x,y), V_{90}(x,y), V_{135}(x,y)\}$$  \hspace{1cm} (3)

Following this, a filtering operation proposed by Miura [12] is conducted to eliminate noise and to connect the center of the IKP line patterns.

3.3.3. Binarization of the IKP feature map. Finally, the IKP feature map is binarized with a threshold. Instead of using a fixed threshold, we determine the threshold with a more robust scheme since the contrast of the feature map may vary greatly. We assume that there are at least 50 pixels belonging to the IKP pattern in each feature map, and the pixels with a greater intensity in the feature map also have higher possibility of belonging to the IKP pattern. Thus, we sort all of the pixels from the feature map in descending order according to their intensity. Then, we calculate the average intensity of the top 50 pixels, denoted as $P_{\text{avr}}$, which represents the overall intensity of the IKP pattern. Further, the threshold can be determined as half of $P_{\text{avr}}$. Therefore, we can obtain the binarized feature map $F(x,y)$. Pixels
with intensities above the threshold are labeled as one; the others are labeled as zero. An example of a feature map is shown in Fig. 6.

![Feature Maps](image)

**Figure 6.** (a) Input image. (b) Feature map. (c) Binarized feature map

### 3.4. Feature matching

The dissimilarity between two given feature maps, $F_1(x, y)$ and $F_2(x, y)$, can be measured by the normalized Hamming distance, which is defined in Eq. (4):

$$
\text{dist}(F_1, F_2) = \frac{\sum_{y=0}^{\text{rows}} \sum_{x=0}^{\text{cols}} (F_1(x, y) \otimes F_2(x, y))}{N_1 + N_2}
$$

Where $N_1$ and $N_2$ denote the number of pixels with a value of 1 in the feature map $F_1(x, y)$ and $F_2(x, y)$, respectively.

Taking into account the possible translation of the IKP feature in the image, multiple matches are made by translating one feature map in the horizontal and vertical directions. The minimum distance is considered to be the final matching distance. In our experiment, the range of horizontal and vertical translations are empirically set as -10 to 10 and -8 to 8, respectively.

### 4. Experiments and results

To evaluate the performance of the proposed IKP recognition system, two experiments are conducted. First, the tolerance to illumination variation of the MMCP method is described. Second, the verification experiment is implemented based on our IKP image database and the error rate is analyzed.

#### 4.1. Tolerance to illumination variation

Tolerance to illumination variation is crucial for a biometrics system. To measure the robustness of the MMCP method against different illumination, several IKP images of the same finger were captured. To ensure the credibility of the test, the volunteer is requested to keep the same finger posture. The illumination is tuned by adjusting the pulse width modulation (PWM) duty cycle of the LED current.

As shown in Fig. 7, the image with a duty cycle of 0.15 has the lowest brightness, and some patterns are not very clear. The image with a duty cycle of 0.80 has the highest brightness, however, some regions of the image are overexposed. In addition, the image with a 0.50 duty cycle has the most appropriate brightness and contrast, and can be used as the standard image.

To quantify the effect of the illumination, we extracted feature maps from all IKP image using MMCP method and compared them with the standard feature map (Fig. 7 (g)). The matching results are shown at the right bottom corner of the corresponding image. Fig. 7 shows that most line patterns can be extracted from the original image robustly against illumination variation, and they contain very little
noise. Regarding the overexposed image, it is almost impossible to extract the line pattern from the overexposed area. In addition, most of the feature maps have short distances compared with the standard feature map. Even images with overexposed areas also have the distance lower than the normal decision threshold, which implies that the MMCP method has decent tolerance under different illumination levels.

![Figure 7](image)

**Figure 7.** IKP images and corresponding feature maps under different illumination levels. The value located in the left bottom corner of the image is the PWM duty cycle of the drive current for fill-in light LED. The value located in the right bottom corner of the image is the normalized Hamming Distance compared with the standard feature map (g).

### 4.2. Verification experiment

To evaluate the accuracy of the proposed IKP recognition system, a verification experiment is conducted based on our IKP image database, which contains 1987 IKP images from 209 different fingers, with 8-10 images per finger. We collected IKP images of index, middle and ring fingers from each hand with the proposed acquisition device. Most of the IKP images are from the researchers and students in our laboratory, ranging in age from 20 to 40, and approximately 2/3 of these are men.

To explain the performance of the proposed system more clearly, we implement an additional three algorithms, namely MCP, CompCode and RLOC. The same image pre-processing is conducted. The feature maps extracted from a real IKP image using various methods are shown in Fig. 8. It can be found that the proposed algorithm can extract the IKP pattern clearly with little noise, while the CompCode and RLOC methods suffer from substantial random noise, especially in the smooth areas of the image. The MCP method can also extract the centreline of the IKP pattern, although part of the centerline is missing owing to random noise.

![Figure 8](image)

**Figure 8.** (a) Input image. (b) MMCP. (c) CompCode. (d) RLOC. (e) MCP
Matching is performed for every pair of images. There are 8691 genuine matches and 1964400 imposter matches in total. Then, the false acceptance rate (FAR) and the false rejection rate (FRR) are calculated. The former means false acceptance to an imposter pair, and the latter means false rejection to a genuine pair. To quantitatively evaluate these results, we use the equal error rate (EER), which is the error rate when FAR equals FRR under a specified threshold. Actually, FAR and FRR are discrete numbers, and there may be no such threshold where FAR equals FRR exactly. Thus, we choose the threshold where |FAR - FRR| is minimized.

Table 1 summarizes the verification results. Our method achieves an EER of 0.36%, performing better than other methods. Moreover, the receiver operating characteristic (ROC) curve is shown in Fig. 9(a), which is a plot of the genuine acceptance rate against FAR for all possible thresholds. This shows our method always has the highest genuine acceptance rate than other methods under the same FAR condition. In the meantime, we can still achieve a 92% genuine acceptance rate when the FAR drops to zero, meaning that the IKP recognition can be a reliable biometric system. The distance distribution obtained by proposed method is shown in Fig. 9(b). Each distribution is normalized by its maximum frequency. This shows that the distance between different fingers is always high, whereas the distance between the same fingers is usually low. Large distances between the same fingers are usually caused by finger deformation, such as finger bending, which should be further investigated.

| Method | EER (%) | FRR when FAR is zero (%) |
|--------|---------|--------------------------|
| CompCode | 0.84 | 13.28 |
| RLOC | 2.13 | 33.61 |
| MCP | 2.90 | 68.32 |
| MMCP | 0.36 | 7.88 |

Figure 9. (a) ROC curves obtained by different IKP recognition algorithm. (b) Hamming distance distribution of the MMCP method

4.3. Speed
The IKP recognition software is developed in python language on a PC equipped with an Intel Core i5 CPU of 2.7GHz and 8GB memory. The total time for image pre-processing and feature extraction is 1.02 s. The average match time per pair is approximately 3.48 ms. Therefore, the entire system can work in real-time even if there are hundreds of feature maps in the registered database. Considering the limited efficiency of the python language, a higher speed is possible by developing the software in other languages such as C/C++. 
5. Conclusion
This paper represents a personal recognition system based on the inner-knuckle-print, which consists of an IKP image acquisition device and an image processing module. The acquisition device is designed with the aim of restricting finger posture in a friendly way. Thus, the scaling transformation of the image is eliminated, although slight rotations and translation transformations still exist. The image recognition system contains three steps: image pre-processing, feature extraction, and feature matching. In the first step, the rotation and translation of the finger is evaluated and corrected. Then, the IKP region is located using Radon projection, followed by an image crop operation. Following this, we employ a modified maximum curvature point method for feature extraction, which can extract the central region of the IKP line pattern robustly against illumination variation. Furthermore, the feature map is binarized with a threshold. We propose a new method for calculating the threshold, which is more robust for feature maps with different contrasts. Finally, the dissimilarity between the feature maps is measured using the normalized Hamming distance.

To evaluate the accuracy of our system, an IKP image database is established, and it contains 1987 different IKP images. The experimental results show that our method achieves an EER of 0.36%, performing better than other traditional methods and the entire system can work in real-time.

Our future work will focus on the multi-modal biometrics system, including designing new acquisition device which can acquire multiple biometric features simultaneously, and developing new recognition algorithm to achieve a higher recognition accuracy.

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