Finger knuckle print recognition based on SURF algorithm

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Abstract—**This paper proposed a knuckle print recognition algorithm based on SURF algorithm. Firstly, a coordinate system is defined based on the local convex direction map of the finger knuckle print(FKP) to align the images and a region of interest (ROI) is cropped for feature extraction; secondly, the key points are extracted with fast Hessian detector, to which an orientation was assigned according to the Haar wavelet responses inside the neighbor circle area of the keypoint; and an orientation invariant descriptor is constructed for each key point. In recognition, testing FKP features are matched to the template features for initial correspondences, then random sample consensus (RANSAC) is employed to establish the geometric constraint which is used to remove false matching. The amount of final matched point pairs is referred to decide the consistency of two palm images. Plenty of experiments show that FKP can be recognized with high accuracy. The method is invariant to rotation, scale and viewpoint changes, which proves its robusticity.**

Keywords- Biometrics; finger knuckle print recognition; SURF; random sample consensus (RANSAC)

I. INTRODUCTION

Biometric identity authentication is playing an important role in public security, access control, which related to application area such as judicature procedure and banks etc [1]. The most frequently used biometric features are finger print, face, iris, signature and gaits etc.

Besides finger print, other hand-based biometrics has attracted lot of attention and personal identification by using palmprint, hand geometry, 3-D finger geometry, and hand vein have been proposed in the literature[2]. Sun et al[3] represented palmprint with orthogonal line ordinal features which achieved significantly high accuracy with low computational cost; Jain et al[4] developed a prototype latent-to-full palmprint matching algorithm which can recognize partial and latent palmprints in full palmprints database with recognition rates of 78.7% and 69% by using minutiae features, the method requires high quality palm images with a resolution of at least 400 dpi. You et al[5] extracted texture feature, global texture energy and interesting points from the palm and then matched in a hierarchical fashion, which achieved adequate performance, while the correlation of different features from the same palm is not considered yet. Zheng et.al[6] presented a projective-invariant representation for hand features to create robust projective permutation invariant(PPI) hand geometry biometrics technology which is peg free, noncontact, and nonintrusive.

Recent study revealed that finger knuckle print are very discriminative[7]. Finger knuckle print (FKP) refers to the outer part of the finger around the phalangeal joint. Zhang *et al.* established and released the PolyU FKP database which make it possible for researchers to work on FKP recognition[8]. A lot of progress on FKP recognition has been achieved in recent years. Kumar *et al.* used localized Radon transform to generate KnuckleCodes which can be used for matching[9]. Zhang *et al.* extracted the image local orientation information with 2D Gabor filters to represent the FKP features[10]. Lin Zhang *et al.*also proposed FKP matching method based on Band-Limited Phase-Only Correlation (BLPOC)[11]. Kumar and Ravikanth also employed PCA, LDA and ICA analysis for finger knuckle print recognition[2].

To explore FKP recognition technology, this paper proposed a robust FKP feature presentation and matching method based on Speeded-Up Robust Features(SURF） [12]. SURF is an improvement on Scale-Invariant Feature Transform(SIFT) [13]. SIFT algorithm is a widely adopted object recognition technique, which is also very effective in implementing face and fingerprint recognition. Compared to SIFT algorithm, SURF uses different keypoint detector and feature descriptor. The keypoint detector is based on the approximation of Hessian matrix, and uses integral images[14] to reduce the computation time, so it can be called the 'Fast-Hessian' detector. The descriptor, on the other hand, describes a distribution of Haar-wavelet responses within the interest point neighbourhood. Again, integral images are used for speed. SURF uses a new indexing step based on the sign of the Laplacian, which increases not only the matching speed, but also the robustness of the descriptor. The entry of an integral image $I_\Sigma(\mathbf{x})$ at a location $\mathbf{x} = (x, y)$ represents the sum of all pixels in the input image $\mathbf{I}$ of a rectangular region formed by the point x and the origin, $I_{\sum}(x) = \sum_{i=0}^{i\le x}\sum_{j=0}^{j\le y} I(i,j)$, With $I_\Sigma(\mathbf{x})$ calculated, it only takes four additions to calculate the sum of the intensities over any upright, rectangular area, independent of its size.

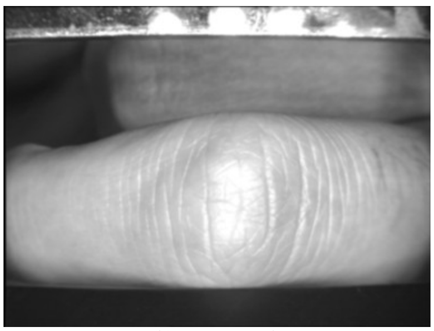
The rest of the paper is organized as follows: Section 2 describes the procedure of FKP image preprocessing; section 3 introduces the FKP feature extraction based on SURF algorithm; Section 4 is the feature matching procedure; Section 5 gives experimental results and finally in section 6 are conclusions and future work.

II. FKP IMAGE PREPROCESSING

The FKP images used in this paper are from the PolyU FKP Database. The FKP acquisition device and captured FKP sample are shown as figure 1. The database has been acquired on 4 fingers of 165 volunteers, leading to 660 different classes.

There is no other database containing as many users. Each class contains 12 images acquired during 2 sessions. The first session, which corresponds to the first six images and the second session corresponds to the last six images.

(a) Acquisition device



(b) FKP sample

Figure 1. FKP acquisition device and FKP sample

The database provides two sets of images. The first one corresponds to the whole acquired image. The second one corresponds to region of interest (ROI) images extracted from the first set of images. The ROI extraction is detailed in[10]. The extracted ROI is shown as figure 2. Before feature extraction, ROI image is normalized to the range 0~255(shown in figure 3).

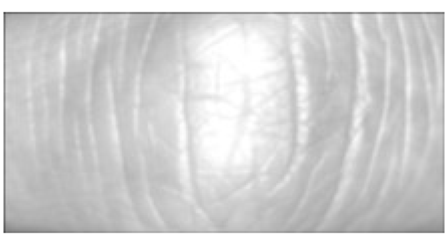


Figure 2 FKP ROI image

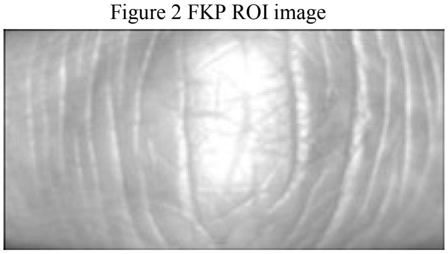


Figure 3 Normalized ROI image

III. SURF FEATURE EXTRACTION

Since the ROI images of FKP are with low definition, the grayscale value changed smoothly in the space. It's hard to detect abundant and stable key points even with difference of Gaussian(DoG) or Harris algorithm.

A. Detecting key points with Fast-Hessian

Hessian matrix key-point detector performs well both in accuracy and in time efficiency. Given a point **p**=(x,y) on image *I*, the Hessian matrix in point **p** at scale σ is defined as :

$$H(p,\sigma)=\begin{bmatrix} L_{xx}(p,\sigma) & L_{xy}(p,\sigma) \\ L_{xy}(p,\sigma) & L_{yy}(p,\sigma) \end{bmatrix} \quad (1)$$

where $L_{xx}(p,\sigma)$ is the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point **p**，and similarly for $L_{xy}(p,\sigma)$ and $L_{yy}(p,\sigma)$.

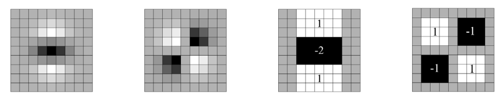
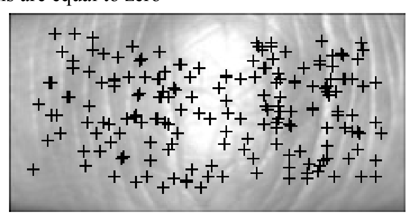
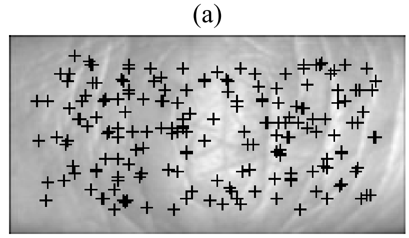


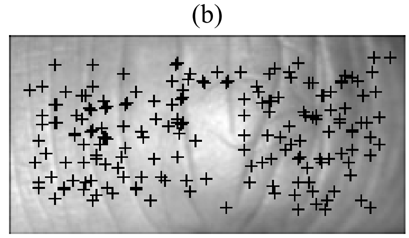
Figure.4 Left to right: the Gaussian second order partial derivatives in y-direction and xy-direction, and the approximations thereof using box filters. The gray regions are equal to zero[12]



(a)



(b)



(c)

Fig.5 Examples of extracted keypoints

The 9 × 9 box filters in figure 4[12] are approximations for Gaussian second order derivatives with σ=1.2. By using integral image, the convolution of image *I* with box filter can be realized with high efficiency. In order to localise interest points in the image and over scales, a non-maximum suppression in a 3 × 3 × 3 neighbourhood is applied. The key points detected from FKP ROI images with Fast-Hessian are shown in figure 5.

B. *Extracting SURF Descriptor*

In order to describe the key-points with distinction to other key-points, SURF describes the key-point based on the dominant orientation of the local region around key-point.

1) Orientation Assignment

Firstly, a circular region is constructed around the extracted key-points. Dominant orientation is computed based on the information from circular region around key-point. The orientation is computed using the Haar wavelet responses in both *x* and *y* directions. The dominant orientation is estimated by summing the wavelet response within a rotating wedge covering an angle of 60^o in wavelet response space. The resulting maximum is considered as dominant orientation and used to describe the key-point. Since the dominant orientation is rotation invariant, the descriptor becomes invariant to image rotation.

2) Descriptor Components

For the extraction of the descriptor, a square region centered around the interest point is constructed and oriented along the dominant orientation. The descriptor is extracted from the aligned squared region. The Square region is partitioned into smaller sub-regions of size 4 × 4. Haar wavelet responses in vertical and horizontal directions are computed for each sub-region. The sum of the wavelet response *dx* and *dy* for each sub-region are used as feature values. Then, the wavelet responses dx and dy are summed up over each sub region and form a first set of entries to the feature vector. In order to bring in information about the polarity of the intensity changes, the sum of the absolute values of the responses, |dx| and |dy|, are also computed. Hence, each sub-region has a four-dimensional descriptor vector $\boldsymbol{V}$ for its underlying intensity structure：

$$V = \left\{ \sum d_x, \sum d_y, \sum |d_x|, \sum |d_y| \right\} \qquad (2)$$

Concatenating the descriptor vectors from all 4x4 sub-regions will compose a descriptor vector with length of 64 which is called SURF descriptor for the key-point.

IV. FKP FEATURE MATCHING

To recognize a FKP image, the SURF descriptor of each key-point computed in the test image is matched to descriptor of every SURF keypoint of the enrolled image in the database. Since the extracted keypoint could be the noise or the non-intrinsic key point brought about by the variation of illumination or pose, the initial matches may be incorrect. Therefore, clusters of at least 3 features are first identified that agree on an object and its pose, as these clusters have a much higher probability of being correct than individual feature matches. Then, each cluster is checked by performing a detailed geometric fit to the model, and the result is used to accept or reject the interpretation.

A. *Keypoint matching*

The best candidate match for each keypoint is found by identifying its nearest neighbor in the database of keypoints from testing images. The nearest neighbor is defined as the keypoint with minimum Euclidean distance for the invariant descriptor vector. However，many features from an image will not have any correct match in the template database because of arising noise or the missing detection of keypoints in the training images. It's necessary to find a way to drop those features. Using a global threshold for Euclidean distance may not be effective because some descriptors are more distinctive than the others. By comparing the distance of the closest neighbor to that of the second closest neighbor, we reserve all matches in which the distance ratio is less than 0.6. Thus the initial tentative correspondences between two keypoint sets of testing image and template are got.

B. *Confirming the match with RANSAC*

Using the number of matched features with the method described in previous section to decide the model consistence between two images is not sufficient. We randomly select three pairs from the correspondences got in section 3.1，to estimate the affine transformation matrix between two keypoint sets. This paper employs the robust method of RANSAC algorithm to estimate the affine transformation matrix $\boldsymbol{H}$：

$$H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \qquad (3)$$

Then check each correspondence with the affine transformation matrix $\boldsymbol{H}$ to find out if the difference between the location of correspondent keypoint and estimated position is inside a tolerance. That is：

$$(x_i' - \frac{h_{11}x_i + h_{12}y_i + h_{13}}{h_{31}x_i + h_{32}y_i + h_{33}})^2 + (y_i' - \frac{h_{21}x_i + h_{22}y_i + h_{23}}{h_{31}x_i + h_{32}y_i + h_{33}})^2 < \delta \qquad (4)$$
$$where \quad i = 1, \ldots, n$$

When the number of correspondences that satisfied with the constraint （eq. 4）is larger than the threshold *m* and the accumulation of the differences between the location of correspondent keypoints and estimated positions is less than another threshold *dmax*, we think two images are matched successfully. Otherwise, repeat the above procedure and re-estimate the Matrix *H*. If the number of correspondences is less than 4 or the matrix *H* is repeatedly estimated for 100 times and none of them can satisfied the constraint, then we think two images are failed in matching. The thresholds *m* and *dmax* are set by experience of experiments.

V. EXPERIMENTAL RESULTS

The FKP images used in this paper are from the PolyU FKP database. We used the middle finger knuckle print images from 165 left fingers to test our algorithm. 12 images are captured from each finger during 2 sessions in which one are used as template and the remaining samples are for testing.

All the experiments are conducted with Visual Studio 2005 and OpenCV on Intel T7400 2.16 GHz, 1G RAM PC. The experimental result is shown in table 1 where verification means an unknown subject is compared against a specific subject in the database to verify his/her identity, while identification means an unknown subject is compared against all the subjects in the database to establish his/her identity.

TABLE I. THE ACCURACY, TIME PERFORMANCE AND TOLERANCE TO IMAGE VARIANCES OF PROPOSED ALGORITHM

	Verification	Identification
Testing rounds	1815	1650
Correct answers	1645	1599
Accuracy/%	90.63	96.91
Average matching time/s	0.531	0.106

We can see from above table that the proposed method performs well both in recognition accuracy and time efficiency. Furthermore, since the SURF features are invariant to image translation, scaling, and rotation, the proposed FKP recognition method has the merit of translation, scaling, and rotation invariance. We tested the algorithm with rotated, scaled, or both rotated and scaled samples and got the expected answers without additional costs. As shown in figure 6, the testing samples rotated 30º(figure 6a), scaled to 90% (figure 6b), rotated 15º and scaled to 90% (figure 6c) are all matched correctly with their templates.

VI. CONCLUSION

FKP recognition provides new way for authentication identity. It has the advantages of easy to capture, short response time, small feature size, low hardware cost no emotional coupling with criminal records. In this paper, we introduce a SURF based feature extraction and RANSAC based matching strategy for FKP recognition. Experiments are carried out in order to measure the performance of the proposed method. It shows that the proposed FKP recognition method is with high performance in terms of accuracy and efficiency on the testing database. Moreover, the method is invariant to image translation, scaling, and rotation, which is very important in pattern recognition. SURF is an attempt to improve SIFT in time performance, and SIFT features have been widely used in image calibration, image repair, automatic panorama image creation and face recognition. The using of SURF in FKP recognition is an exploration for new application of SURF algorithm, which can be used in entry control , attendance recording and security system of banks for identity authentication.

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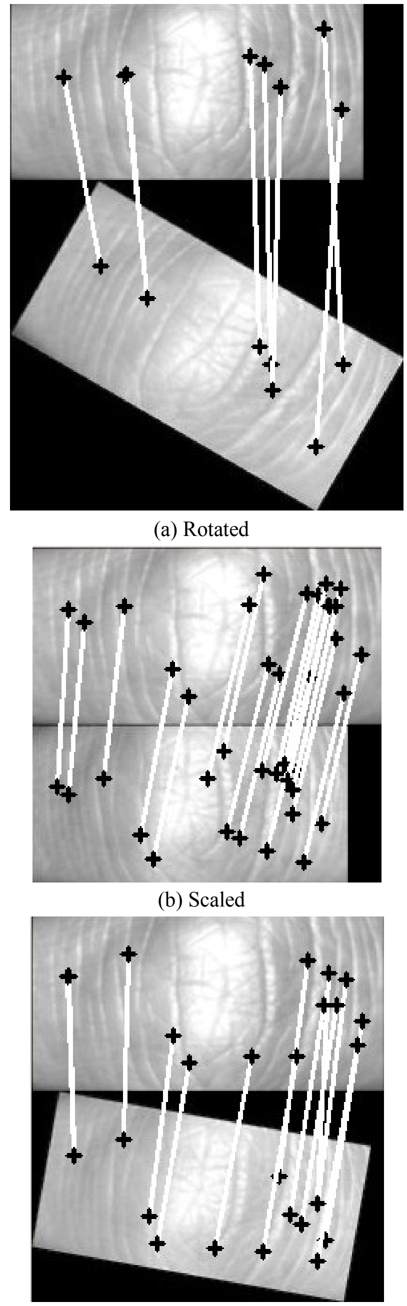

(a) Rotated

(b) Scaled

(c) Rotated and scaled

FIGURE 6. RECOGNIZE ROTATED OR/AND SCALED IMAGES

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