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# Fuzzy based finger vein recognition with rotation invariant feature matching

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**Abstract.** Finger vein recognition is a promising biometric with commercial applications which is explored widely in the recent years. In this paper, a finger vein recognition system is proposed using rotation invariant feature descriptors for matching after enhancing the finger vein images with an interval type-2 fuzzy method. SIFT features are extracted and matched using a matching score based on Euclidian distance. Rotation invariance of the proposed method is verified in the experiment and the results are compared with SURF matching and minutiae matching. It is seen that rotation invariance is verified and the poor quality issues are solved efficiently with the designed system of finger vein recognition during the analysis. The experiments underlines the robustness and reliability of the interval type-2 fuzzy enhancement and SIFT feature matching.

## 1. Introduction

The outdated authentication systems based on password and personal identification number (PIN) has been successfully replaced by biometrics in the modern era. Finger vein recognition is an economic and easy to use biometrics with commercial applications. Finger vein biometrics requires tracing of vein patterns hidden beneath the skin of human finger which can be seen only with the help of some specific imaging devices and hence is extremely resilient against forgery.

The vein patterns inside the fingers are captured using a CCD camera by exposing the finger to near infrared rays of 760 to 1000 nm wavelength. The infrared light is taken up by the haemoglobin in the finger vein which makes the vein pattern look darker than the other regions in the image. In practice, the captured vein images are of inferior quality due to low contrast and optical blurring because of light scattering. Hence efficient enhancement techniques and reliable matching algorithms are essential in finger vein recognition.

Finger vein technology has been explored by Hitachi Ltd. of Japan since 1997. Finger vein structure was proposed as an innovative system for identification of individuals by Kono [1] from the medical systems researcher department of Hitachi Ltd, Japan. Yangawa [2] studied the efficacy of finger vein patterns in personal identification with the help of a database consisting of 2024 images from fingers of 506 people. Kumar [3] used Gabor transform in their research and published a database. In order to enhance the finger vein images various techniques of enhancement have been used by different researchers. Various Gabor filters [4, 5] have been used for finger vein enhancement. Histogram equalization [6] is another refined method for enhancing the contrast of a finger vein image. Fuzzy techniques have been successfully implemented in finger vein enhancement by many researchers. Cheng-Bo Yu [7] suggested an image enhancement algorithm based on fuzzy theory. An



image fusion procedure based on fuzzy has been developed by Kwang Yong Shin [8] which enhanced the image quality.

During the initial years of finger vein biometric research most of the researchers applied vein template directly as a feature for matching [9, 10]. E.C. Lee [11] and B.A. Rosdi [12] suggested finger vein matching using local binary pattern. Cheng Bo Yu [13] used modified Hausdorff distance between the minutiae points from the vein patterns. Fei Liu [14] presented a minutiae matching based on singular value decomposition. Scale invariant feature transforms introduced by D.G. Lowe [15] is a local feature description algorithm relying on scale space. J. Peng [16] proposed finger vein matching by extracting SIFT features after applying Gabor filters. H.G. Kim [17] suggested an illumination normalization before extracting SIFT features from the finger vein images.

In this paper, finger vein images in the biometric database are subjected to an enhancement based on type-2 fuzzy theory before extracting the features for matching. Enhanced images undergoes a feature extraction process which is invariant to rotation. Using a threshold based on a matching score, the images are either accepted or rejected.

## 2. Image processing with fuzzy set theory

Representing an image using fuzzy set theory is an efficient strategy for handling the ambiguity and imperfection associated with the image. Fuzzification of image, modification of the membership values and defuzzification of image are the three main stages involved in fuzzy image processing.

Fuzzy systems consider image pixels as fuzzy sets [18]. The fuzzy theoretic form of an image  $I$  can be given as,  $I = \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} [p_{ij}, \mu_I(p_{ij})]$  where the size of the image is  $P \times Q$  with  $L$  levels and  $p_{ij}$  is the gray level at the pixel position  $(i, j)$  with membership value  $\mu_I(p_{ij})$  where  $i$  varies from 0 to  $P - 1$  and  $j$  from 0 to  $Q - 1$ .

## 3. Interval type-2 fuzzy sets

A fuzzy set in which fuzzy sets appear as membership values is called a type-2 fuzzy set [19]. The three-dimensional membership of a type-2 fuzzy set delivers more degrees of freedom for adjusting uncertainties. A type-2 fuzzy set, denoted by  $\tilde{A}$  possesses a membership function  $\mu_{\tilde{A}}(t, u)$  of type-2, where  $t \in X$  and  $u \in J_t \subseteq [0, 1]$ .

$$\text{i.e. } \tilde{A} = \{((t, u), \mu_{\tilde{A}}(t, u)), t \in X, \forall u \in J_t \subseteq [0, 1]\}$$

When the secondary membership in a type-2 fuzzy set becomes unity it is called an interval type-2 fuzzy set [20]. In a type-2 fuzzy set  $\tilde{G}$  if  $\mu_{\tilde{G}}(x, v) = 1, \forall x \in X$  and  $v \in J_x \subseteq [0, 1]$ , then  $\tilde{G}$  is an interval type-2 fuzzy set. i.e.  $\tilde{G} = \{((x, v), 1) / x \in X, \forall v \in J_x \subseteq [0, 1]\}$ .

The footprint of uncertainty (FOU) of an interval type-2 fuzzy set  $\tilde{G}$  is bounded by the upper membership function (UMF) and lower membership function (LMF). The upper bound of  $FOU(\tilde{G})$  is given by the UMF and is represented by  $U(p_{ij})$  and the lower bound of  $FOU(\tilde{G})$  is symbolised by the LMF which is denoted by  $L(p_{ij})$ .

## 4. Proposed method

### 4.1. Image enhancement using interval type-2 fuzzy sets

After extracting the region of interest (ROI) by adequate cropping, each image pixel is fuzzified using a suitable type-1 membership function. Let  $A$  be the finger vein image of size  $M \times N$ . The image is fuzzified by assigning a fuzzy membership value  $\mu_A(p_{ij})$  to the grey level  $p_{ij}$  using,

$$\mu_A(p_{ij}) = \frac{p_{ij} - \alpha}{\beta - \alpha} \quad (1)$$

where  $\alpha$  and  $\beta$  are the smallest and the greatest values of grey levels of the pixels in the image.

We obtain the upper membership function  $U(p_{ij})$  and lower membership function  $L(p_{ij})$  of the interval type-2 fuzzy set by applying a fuzzy linguistic hedge and the reciprocal on the type-1 membership values  $\mu_A(p_{ij})$  of each pixel. They are given by the following equations:

$$U(p_{ij}) = [\mu_A(p_{ij})]^\pi \quad (2)$$

$$L(p_{ij}) = [\mu_A(p_{ij})]^{-\frac{1}{\pi}} \quad (3)$$

In this experiment the value of  $\pi$  is taken as 0.5. As a next step, the upper and lower membership degrees are combined for type reduction using the Einstein T-conorm given by the equation,

$$E(p_{ij}) = \frac{U(p_{ij}) + L(p_{ij})}{1 + [U(p_{ij}) \cdot L(p_{ij})]} \quad (4)$$

The image with the modified membership function is the enhanced image which appears to be clearer and brighter.

#### 4.2. SIFT feature extraction

Scale Invariant Feature Transform (SIFT) convert image statistics into scale invariant coordinates based on local features. In order to construct a scale space SIFT algorithm use Gaussian kernel  $G(i, j, \sigma)$  with scale  $\sigma$  given by (6) and convolute with the image  $I(i, j)$  as in (5)

$$L(i, j, \sigma) = G(i, j, \sigma) * I(i, j) \quad (5)$$

$$G(i, j, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{i^2 + j^2}{2\pi\sigma^2}\right) \quad (6)$$

A difference of Gaussian (DoG) pyramid is obtained by finding its difference from an image whose scale is  $m$  times of original. DoG of each point is compared with its 26 neighbourhood points and it is taken as stable key point of extrema which is scale invariant.

Key points with low contrast are eliminated by excluding the points whose Laplacian value is below a threshold value. Gradient magnitude  $m(i, j)$  and orientation  $\theta(i, j)$  are calculated in a region around the key point location using the Gaussian smoothed images. A 36 bin orientation histogram weighted by gradient magnitude and Gaussian window is formed with  $\sigma$  having one and a half times the key point scale. For any histogram peak within 80% of highest peak, a separate descriptor for each orientation with the same scale and location is created. This aids in invariance to rotation. A 128 dimensional feature description is obtained from the 16 sub regions which are the SIFT feature point descriptors.

#### 4.3. Matching of SIFT feature points

Once the SIFT feature points are extracted from the database image and the query image, feature matching is performed by evaluating the Euclidean distance between the SIFT points of the two images. Matching pairs are selected from all the possible pairs of detected features based on a threshold. A matching score is calculated as given in (7).

$$S(I_D, I_Q) = \frac{N_{DQ}}{\text{Max}(N_D, N_Q)} \quad (7)$$

Here  $N_{DQ}$  is the number of matching pairs between the database and query image features.  $N_D$  and  $N_Q$  denote the number of feature points detected from the database image and query image respectively. Using matching score each pair of images is either accepted or rejected based on a threshold.

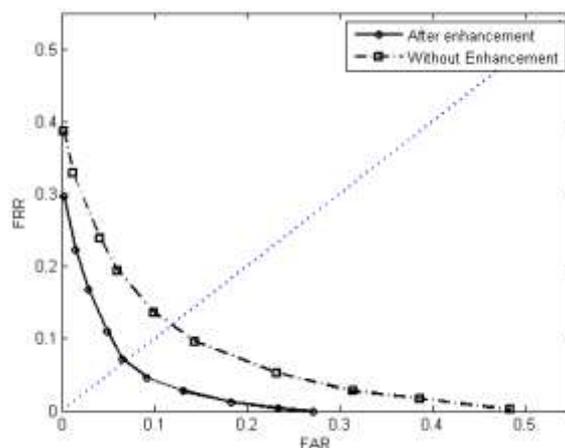
### 5. Experimental results

A performance analysis of the proposed method is done in this section. The suggested algorithm is applied on finger vein images and the performance is compared with some existing matching techniques. Hong Kong Polytechnic University finger vein database (version 1.0) [21] has been used for the experiment and assessment. For data acquisition vein pattern images of index and thumb fingers in the left hand of 156 subjects were captured using a contactless imaging device.

The performance of the proposed system was evaluated by computing equal error rate (EER), False acceptance rate (FAR), False rejection rate (FRR) and tracing the receiver operating characteristic (ROC) curve. The total performance of the biometric system can be analysed based on EER which gives the error rate by considering FRR and FAR equally. In this work, 20 equally spaced threshold values were used and FAR and FRR values were noted for each threshold. ROC curve was plotted with FAR values on the X axis and FRR on the Y axis. On the ROC curve, the common error at which FAR and FRR were equal was noted as EER. FRR at zero FAR and FAR at zero FRR were also recorded.

ROC curve of the proposed SIFT matching algorithm plotted before doing the interval type-2 fuzzy enhancement and after the enhancement in figure 1. Table 1 provides the EER, FRR at zero FAR and FAR at zero FRR for the two cases. Figure 1 depicts the relation between FAR and FRR which clearly indicates that the proposed SIFT matching after the fuzzy enhancement gives better results than the matching without enhancement. Both FAR and FRR of proposed method are lower at each threshold values. From table 1, EER of the proposed algorithm is 0.0567 while it is 0.1196 for matching without the fuzzy enhancement. Table 1 also shows lower values of FRR at zero FAR and FAR at zero FRR for the proposed SIFT matching.

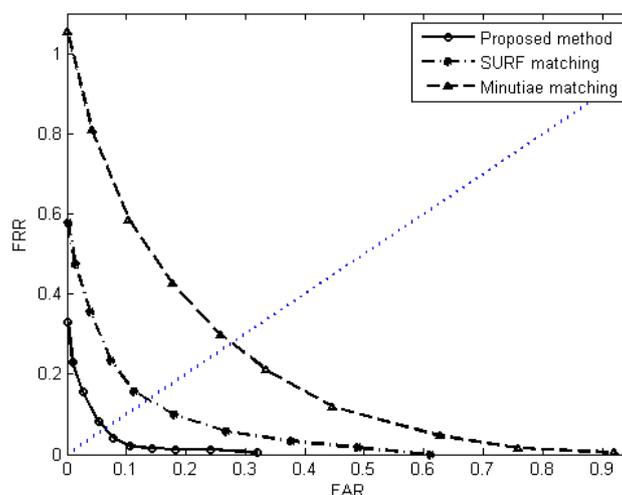
In order to demonstrate the advantage of rotation invariance of the proposed SIFT matching we conducted the same experiment with simulated database by rotating the source database. For rotation database the finger vein images in the source database were rotated 5° clockwise. Figures 2 shows the ROC curves of the different methods for the rotation databases. EER, FRR at zero FAR and FAR at zero FRR for the three methods for the database is listed in table 2. EER of the SIFT matching is 0.9563 which is much lower than that of the other two methods in the rotation database. FRR at zero FAR and FAR at zero FRR for rotation database is lesser for the proposed technique. This section of the experiment is a valid confirmation for the rotation invariance of the SIFT matching.



**Figure 1.** ROC curve for SIFT matching

**Table 1.** Performance evaluation of SIFT matching before and after enhancement

SIFT matching		EER	FAR at zero FRR	FRR at zero FAR
Without enhancement	fuzzy	0.1196	0.4942	0.3902
After enhancement	fuzzy	0.0567	0.2718	0.2998



**Figure 2.** ROC curve of the different methods using the rotation database

**Table 2.** Performance evaluation of different methods using the rotation database

	EER	FAR at zero FRR	FRR at zero FAR
Proposed Method	0.0553	0.3216	0.3512
SURF matching	0.1330	0.5982	0.5915
Minutiae matching	0.2763	0.9243	1.0541

## 6. Conclusion

In the proposed work, invariance of feature matching is verified using a simulated rotation database of finger vein images after enhancing the images with an interval type-2 fuzzy method. Einstein T-conorm is used in the aggregation of type-2 fuzzy sets. A matching score based on Euclidean distance is used for scale invariant feature matching. From the experiments, it is evident that error rates are considerably low after enhancing the image by the proposed algorithm. The efficiency of the suggested method in rotation invariance is also verified in comparison with the existing algorithms.

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