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A smart computing algorithm for finger vein matching with affine invariant features using fuzzy image retrieval

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Abstract

Finger vein recognition is a recently explored biometric system, renowned for its accuracy and reliability. Even though finger vein biometric system possesses exceptional qualities against other biometrics, it is quite challenging to extract enough number of reliable and consistent features for matching. Due to light scattering and other irregularities in the imaging procedures, finger vein images often possess random distortions and affine issues. In this paper, efficiency of affine invariant feature matching is investigated in the framework of finger vein biometrics. In order to reduce the time complexity of the affine invariant features, a size reduction of the database is attained through fuzzy based image retrieval. The experiment results shows better performance after the retrieval and much lower error rates in comparison with the existing feature matching algorithms.

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*Keywords:*Finger vein biometric; Affine invariant feature matching; Image retrieval; Fuzzy set theory

1. Introduction

Finger vein biometrics is being recognised worldwide as a highly accurate biometrics. It is proven that the vein pattern of human finger is unique to each individual [1] which is not affected by race, skin colour or external changes like roughness or damage of the skin. Being an internal feature, it does not leave any traces behind which could be used to replicate the vein pattern. Moreover, the necessity of live finger for authentication makes it robust

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against spoofing. Another advantage of finger vein recognition in a hygienic viewpoint is that the finger need not be in contact with the sensor [2].

Whileimage capturing, haemoglobin in blood veins absorbs infrared light from light source [3, 4]. Vein image is captured as a pattern of shadows by the charge-couple device (CCD) monochrome camera kept on the other side of the finger [5, 6]. After normalizing the captured images, they are stored as a template in the finger vein biometric database.

Each time during finger vein identification, vein image of user is compared against stored templates in the database. Finger vein verification is a process of determining whether the finger vein image given by the user is same as his stored template. Finger vein identification is a one to many comparison where a finger vein template is retrieved from the database which corresponds to the query image. Even though finger vein biometric system possesses exceptional qualities against other biometrics, it is quite challenging to extract enough number of reliable and consistent features for matching. Due to light scattering and other irregularities in the imaging procedures, finger vein images often possess random distortions and affine issues. These affine issues can be effectively tackled by using affine invariant features during the feature extraction stage which will result in reliable biometric identification. Affine transformation features are used in ASIFT feature matchingwhich can provide resistance to robust affine issues and thereby better matching results.Scale invariant feature transforms introduced by D.G. Lowe [7] is a local feature description algorithm relying on scale space. J Peng [8] proposed finger vein matching by extracting SIFT features after applying Gabor filters. H.G. Kim [9] suggested an illumination normalization before extracting SIFT features from the finger vein images.ASIFT feature matching was introduced by J.M. Morel [10] who used affine invariant parameters which resist persistent affine characteristics.

Content based image retrieval makes use of the visual traits of an image to characterize and index the images. Feature vectors of database imagesare compared with that of the query image after forming a feature vector database of images. Image retrieval is executed with the support of an indexing system after calculating the similarity measures or distance measures. This image retrieval stage reduces the computation burden and aids in faster feature matching.Content based image retrieval aims to retrieve images from a huge database by analyzing their visual features. Numerous image retrieval systems have been established effectively in the recent era, SIMPLIcity System [11], Blobworld System [12] and Visual SEEK [13].Many modern intelligent systems have adopted fuzzy set theory proposed by Zadeh [14] because of its human like reasoning and efficiency. Chen and Wang [15] used a region based fuzzy approach with feature matching for image retrieval. Krishnapuram [16] proposed a fuzzy retrieval system for images (FIRST) which incorporates relational graphs that are fuzzy attributed (FARG) for image representation. Konstantinidis [17] developed fuzzy linking method of color histogram creation which contains only 10 bins for recovering like images from an assorted image collection. Iqbal [18] used a retrieval approach for biometric security with image features measured by fuzzy heuristics.

In this paper, efficiency of affine invariant feature matching is investigated in the framework of finger vein biometrics by using ASIFT feature matching. In order to reduce the time complexity of the affine invariant features, a size reduction of the database is attained through fuzzy based image retrieval.

2. Fuzzy image retrieval of finger vein database images

2.1. Fuzzification of images

A few significant images from database are retrieved at this stage, in decreasing order of similarity with the query image. In order to use fuzzy measures, intensity levels need to be shifted to a fuzzy plane where the intensity values are modified as real numbers between 0 and 1. Alteration of crisp values into fuzzy values for the linguistic fuzzy sets comes under fuzzification. Each linguistic term is associated to a grade by a membership function. By fuzzification, we mean the process of converting an object into a fuzzy object. A crisp set may be fuzzified by attaching a membership grade to each element of the set.

For fuzzifying database images and query image, gamma membership function [19] is used here on the histogram count of the intensity levels in images. Each pixel in the image is fuzzified by fuzzifying the corresponding intensity level's histogram count using the gamma function given by equation (1).

$$\mu_D\left(x_j\right)=e^{-K\left|D_h(j)-Q_h(j)\right|} \quad (1)$$

Here $D_h\left(j\right)$ and $Q_h\left(j\right)$ represent histogram counts of intensity level j of database and query images respectively. It is clear that j varies from 0 to $L-1$ if there are L levels of intensity. The constant K in equation (1) is computed by the equation (2). It is defined in such a way that fuzzy membership values given by equation (1) lies between 0 and 1. For this, the largest histogram count of each grey level is noted and then considering all the images in the database, the highest of all these largest histogram counts is taken as H_D. In a similar way, the lowest value of all the smallest histogram counts is noted as L_D. Equation (2) is use for computing the constant K.

$$K=\frac{1}{H_D-L_D} \quad (2)$$

2.2. Retrieval of fuzzified images

In this work, we have proposed a fuzzy set theoretic similarity measure inspired by Tversky's concept of similarity feature. Tversky [20] suggested similarity for matching of features. Measures of similar and dissimilar features and their linear combinations were proposed as similarity.

Let the entities under investigation be represented by $W=\{p,q,r\ .....\}$. Let the objects p, q, and r be characterised by the set of attributes denoted by P, Q, and R. Then similarity measure between the fuzzified database images $\mu_D\left(i\right)$ and query image $\mu_Q\left(i\right)$ can be obtained as equation (3).

$$S\left(D,Q\right)=\frac{\sum_{i=1}^{L}\mu_D\left(i\right)\cap\mu_Q\left(i\right)}{\sum_{i=1}^{L}\mu_D\left(i\right)\cap\mu_Q\left(i\right)+b\sum_{i=1}^{L}\mu_D\left(i\right)\cap\left(1-\mu_Q\left(i\right)\right)+c\sum_{i=1}^{L}\mu_Q\left(i\right)\cap\left(1-\mu_D\left(i\right)\right)} \quad (3)$$

Using algebra of fuzzy sets, intersection $\cap$ can be replaced by any triangular norm (T-norm) operators for better results. Here Einstein T-norm is used as intersection operator whose general form is given by equation (4).

$$E\left(d,q\right)=\frac{dq}{1+\left(1-d\right)\left(1-q\right)} \quad (4)$$

In the case of the database and query fuzzy sets, it takes the form given in equations (5), (6) and (7).

$$\mu_D\left(i\right)\cap\mu_Q\left(i\right)=\frac{\mu_D\left(i\right)\ \mu_Q\left(i\right)}{1+\left(\left(1-\mu_D\left(i\right)\right)\left(1-\mu_Q\left(i\right)\right)\right)} \quad (5)$$

$$\mu_D\left(i\right)\cap\left(1-\mu_Q\left(i\right)\right)=\frac{\mu_D\left(i\right)\left(1-\mu_Q\left(i\right)\right)}{1+\left(\left(1-\mu_D\left(i\right)\right)\ \mu_Q\left(i\right)\right)} \quad (6)$$

$$\mu_Q\left(i\right)\cap\left(1-\mu_D\left(i\right)\right)=\frac{\mu_Q\left(i\right)\left(1-\mu_D\left(i\right)\right)}{1+\left(\left(1-\mu_Q\left(i\right)\right)\ \mu_D\left(i\right)\right)} \quad (7)$$

For each database image, the similarity measure with the query image is given by equation (3) which is calculated using equations (5), (6) and (7) where the parameter values $b=0.5$ and $c=0.5$ as the relative importance to the distinctive features are the same. After calculating similarity for all the images in the database, a subset R of image database D is retrieved based on the similarity value which consists of the best matches to the query image. If R has n images, then $S\left(A,Q\right)\le S\left(B,Q\right)$ for any image A in the subset R and for any image B in the set $D-R$.

3. Affine invariant feature matching

3.1. ASIFT feature extraction

Affine Scale Invariant Feature Transform (ASIFT) convert image statistics into affine invariant coordinates based on local features. Transformation of rotation is introduced by exciting the optical axis rotation of camera in ASIFT for images. After that a tilt operation in the direction of x axis is performed for obtaining affine images in succession. The longitude and latitudeangle transformation is performed inside a certain range for achieving the both tilt and rotation transformations.After these, ASIFT detects key points, and establishes description from the affine image.

In order to construct a scale space the algorithm use Gaussian kernel $\boldsymbol{G(i,j,\sigma)}$ with scale $\boldsymbol{\sigma}$ given by (9) and convolute with the image $I(i,j)$ as in (8)

$$L(i,j,\sigma) = G(i,j,\sigma)*I(i,j) \tag{8}$$

$$G(i,j,\sigma) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{i^2+j^2}{2\pi\sigma^2}\right) \tag{9}$$

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 which are the 8 pixels adjacent to it at the same scale, 9 neighbourhood points each at the scales above and below it. If this particular point has a maximum or minimum value compared to these 26 neighbourhood values, then it is taken as stable key point of extrema which is scale invariant.

For reducing the number of selected steady key points further, the points which are low in contrast and poorly localized are again removed. Key points with low contrast are eliminated by excluding the points whose Laplacian value is below a threshold value. In order to remove the low localized points, the algorithm uses 2x2 Hessian matrix at the location and scale of the key point. These points have a large principle curvature along the edge but, in the perpendicular direction the curvature is small. These large and small principal curvature values are proportional to the maximum and minimum Eigen values of the Hessian matrix. If the ratio between the maximum and minimum Eigen values is greater than a threshold which is usually 10, then the key point is rejected.After that an orientation is assigned to each key point and hence the key point descriptor can be characterized relative to this orientation and rotation invariance can be assured.

An orientation histogram with 36 bins weighted by gradient magnitude and Gaussian window with $\boldsymbol{\sigma}$ equal to 1.5 times the scale of key point is formed. Dominant orientation is taken as the orientation of the key point. 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. Now for creating key point descriptor, a 16x16 neighbourhood with key point as centre is chosen which is further divided into sub regions of size 4x4. An eight dimensional vector is generated in each sub regions by choosing eight directions. Thus a 128 dimensional feature description is obtained from the 16 sub regions which are the ASIFT feature point descriptors.

3.2. Matching of ASIFT feature points

Once the ASIFT feature points are extracted from the database image and the query image, feature matching is performed by evaluating the Euclidean distance between the ASIFT points of the two images. The distance between two points $a = (a_1, a_2, \ldots a_n)$ and $b = (b_1, b_2, \ldots b_n)$ in a Euclidean n-space are given by (10).

$$d(a,b) = \sqrt{\sum_{j=1}^{n} (a_j - b_j)^2} \tag{10}$$

Matching pairs are selected from all the possible pairs of detected features based on a threshold. A matching score is calculated on the basis of the ratio of the number of matching pairs and the number of all detected features from the database and query images as given in (11).

$$S\left(I_D,I_Q\right)=\frac{N_{DQ}}{Max\left(N_D,N_Q\right)} \tag{11}$$

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. Matching Score varies between 0 and 1, where a score closer to 0 indicates a better match.

4. Experimental results

For experiments and evaluation, open database of finger veins acquired by the biometric research centre of Hong Kong Polytechnic University [21] has been used in this work. Performance of the proposed algorithm is compared with existing feature matching techniques like SURF and SIFT matching using the database images.A PCwith 1.70 GHz CPU and 4.0 GB memory is used for the work and experiments are conducted using theMATLAB 7:14:0 platform.

The database consists of 6264 images taken from 156 subjects.Image of vein pattern in the index and thumb fingers of left hands of subjects have been taken during enrolment of database images. For the present experiments, only 6 index finger image samples each from105 subjects have been used. If the 6 samples from one finger is assumed as one class then 105 classes of images were taken in total. The intra class pairs were considered as genuine pairs and inter class pairs of images were taken as imposter pairs.

Equal error rate (EER), False acceptance rate (FAR), False rejection rate (FRR) and tracing the receiver operating characteristic (ROC) curve were used for evaluating and comparing the performance of the proposed system and existing algorithms.

For one query image, a smaller set of images is retrieved from the entire database images which are most similar to the query image using the proposed fuzzy retrieval algorithm. ASIFT features are extracted only from these retrieved images in the proposed method instead of the entire database. Matching score has been used for accepting or rejecting each pair after defining a threshold. Number of accepted imposter pairs and the number of rejected genuine pairs are noted and FAR and FRR are calculated.FAR is ratio of the number of accepted imposter pairsto the total number of imposter pairs whereas FRR gives the ratio of the number of rejected genuine pairs to the total number of genuine pairs. FAR values are plotted on the X axis and FRR on the Y axis on the ROC curve for varying thresholds. On the ROC curve, the common error at which FAR and FRR were equal is noted as EER. FRR at zero FAR and FAR at zero FRR are also recorded.

Fig. 1 shows the ROC curve of the proposed ASIFT matching algorithm plotted without doing the fuzzy retrievalusing the entire database images and after reducing the database using image retrieval.Fig.1 portrays the recognition capacity of the proposed matching after the fuzzy retrievalin comparison with the matching without retrieval.After fuzzy retrieval, EER of matching has come down to 0.3291 and this indicates the efficient influence of retrieval stage.Both FAR and FRR of proposed method are seen to be lower at each threshold values. The different error rates of the proposed algorithm is explicitly given in Table 1 against the error rates of ASIFT feature matching without doing the retrieval section.

Table 1. Performance evaluation in terms of error rates for ASIFT feature matching after the fuzzy retrieval in comparison with ASIFT feature matching without a retrieval stage

	EER	FAR with zero FRR	FAR with zero FRR
Matching without fuzzy retrieval	0.6504	0.2488	0.2717
Matching after fuzzy retrieval	0.3291	0.1703	0.1791

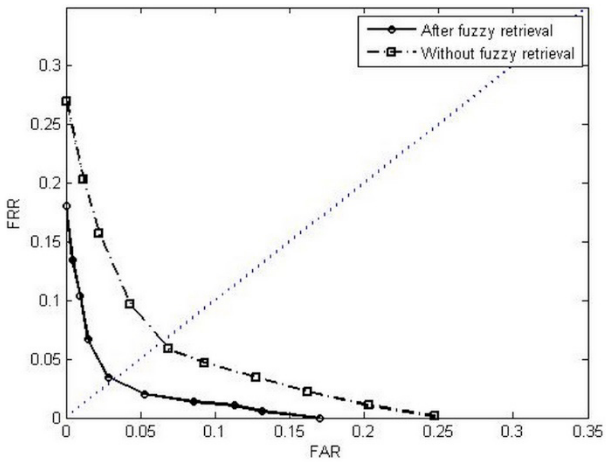

Fig. 1. Performance of ASIFT feature matching without fuzzy retrieval and after fuzzy retrieval

ROC curve of the proposed ASIFT matching algorithm is compared with that of SURF matching and SIFT matching in Fig.2. The EER of ASIFT matching is 0.3300 whereas SIFT shows 0.7160 and SURF gives 1.2460 meaning that ASIFT has much better accurate recognition in all the methods. The error rates are tabulated in Table 2 which gives clear indication about the efficiency of the proposed method. Both FAR and FRR of proposed method are lower than that of other methods at each threshold values. Compared to SURF matching, SIFT matching shows better performance.

Table 2. Comparison of error rates of existing matching algorithms with the proposed ASIFT feature matching with a fuzzy retrieval

	EER	FAR with zero FRR	FAR with zero FRR
SURF feature matching	1.2460	0.4683	0.4881
SIFT feature matching	0.7160	0.2478	0.2967
ASIFT feature matching	0.3300	0.1718	0.1825

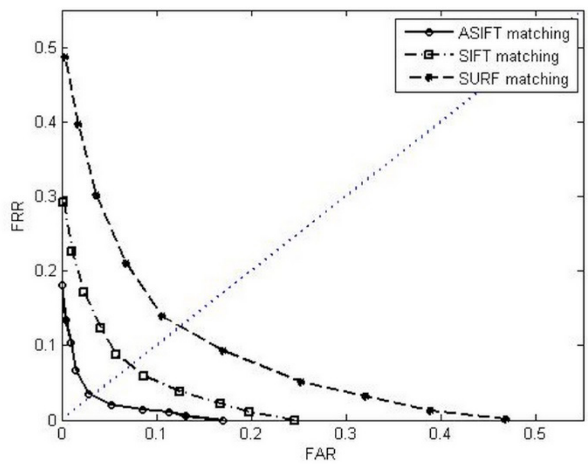

Fig. 2. Comparison of ASIFT feature matching with SIFT and SURF feature matching

5. Conclusion

In this work, a smart computing algorithm using ASIFT feature matching for finger vein biometric system is proposed with a fuzzy based image retrieval.Feature matching demands heavy computational cost, especially when matching is performed against a large database of finger vein images. In order to reduce this computational cost, this paper proposes a retrieval stage prior to the matching procedure where the large database is reduced to a small set of top best similar images using a fuzzy measure. From the retrieved images affine transformation features are extracted for exact matching which can provide resistance to robust affine issues and thereby better matching results.Significanceof retrieval stage prior to matching is confirmed using the experimental results of feature matching before and after retrieval. The proposed algorithm is also compared with SIFT and SURF feature matching and it is verified that the proposed ASIFT feature matching shows better performance in terms of error rates.

References

1. Kono, Miyuki, Hironori Ueki, and Shin-ichiroUmemura. (2000) "A new method for the identification of individuals by using of vein pattern matching of a finger." *Proceedings of the 5th symposium on pattern measurement*, Yamaguchi, Japan 9-12.
2. Yanagawa, Takashi, Satoshi Aoki, and TetsujiOhyama. (2007) "Human finger vein images are diverse and its patterns are useful for personal identification." *MHF Prepr. Ser* **12**: 1-7.
3. Miura, Naoto, Akio Nagasaka, and TakafumiMiyatake. (2004) "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification." *Machine Vision and Applications* **15(4)**: 194-203.
4. Hashimoto, Junichi.(2006) "Finger vein authentication technology and its future." *VLSI Circuits, Digest of Technical Papers* 5-8.
5. Mulyono, David, and Horng Shi Jinn. (2008) "A study of finger vein biometric for personal identification." *Biometrics and Security Technologies,*1-8.
6. Himaga, Mitsutoshi, and Katsuhiro Kou. (2008)"Finger vein authentication technology and financial applications." *Advances in Biometrics* 89-105.
7. Lowe, David G. (1999) "Object recognition from local scale-invariant features." *Computer vision, The proceedings of the seventh IEEE international conference* **2** :1150-1157.
8. Peng, Jialiang, Ning Wang, Ahmed A. Abd El-Latif, Qiong Li, and XiamuNiu. (2012) "Finger-vein verification using Gabor filter and sift feature matching." In *Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), Eighth International Conference on*, 45-48.
9. Kim, Hwi-Gang, Eun Jung Lee, Gang-Joon Yoon, Sung-Dae Yang, EuiChul Lee, and Sang Min Yoon. (2012) "Illumination normalization for SIFT based finger vein authentication." In *International Symposium on Visual Computing*, 21-30.
10. Morel, Jean-Michel, and Guoshen Yu. (2009)"ASIFT: A new framework for fully affine invariant image comparison." *SIAM Journal on Imaging Sciences* **2(2)**: 438-469.
11. Wang, James Ze, Jia Li, and Gio Wiederhold. (2001)"SIMPLIcity: Semantics-sensitive integrated matching for picture libraries." *IEEE Transactions on pattern analysis and machine intelligence* **23(9)**: 947-963.
12. Carson, Chad, Megan Thomas, Serge Belongie, Joseph M. Hellerstein, and Jitendra Malik. (1999) "Blobworld: A system for region-based image indexing and retrieval." In *International Conference on Advances in Visual Information Systems*509-517.
13. Smith, John R., and Shih-Fu Chang. (1997) "VisualSEEk: a fully automated content-based image query system." *Proceedings of the fourth ACM international conference on Multimedia* 87-98.
14. Zadeh, L.A.(1965) "Fuzzy sets."*Information and control* **8 (3)**: 338-353.
15. Chen, Yixin, and James Ze Wang. (2002)"A region-based fuzzy feature matching approach to content-based image retrieval." *IEEE transactions on pattern analysis and machine intelligence* **24(9)**: 1252-1267.
16. Krishnapuram, Raghu, Swarup Medasani, Sung-Hwan Jung, Young-Sik Choi, and Rajesh Balasubramaniam.(2004)"Content-based image retrieval based on a fuzzy approach." *IEEE transactions on knowledge and data engineering* **16(10)**: 1185-1199.
17. Konstantinidis, K., A. Gasteratos, and I. Andreadis.(2005) "Image retrieval based on fuzzy color histogram processing." *Optics Communications* **248 (4)**: 375-386.
18. Iqbal, Kashif, Michael O. Odetayo, and Anne James. (2012)"Content-based image retrieval approach for biometric security using colour, texture and shape features controlled by fuzzy heuristics." *Journal of Computer and System Sciences* **78 (4)**: 1258-1277.
19. Chaira, Tamalika, and Ajoy Kumar Ray. (2003)"Segmentation using fuzzy divergence." *Pattern Recognition Letters* 24 (12): 1837-1844.
20. Tversky, Amos. (1977)"Features of similarity." *Psychological review* **84 (4)**: 327.
21. The Hong Kong Polytechnic University finger image database (version1.0) http://www4.comp.polyu.edu.hk/~csajaykr/fvdatabase.htm