Finger-vein Pattern Recognition Based on ICP on Contours

P. Normakristagaluh
Faculty of EEMCS
University of Twente, Netherlands
p.normakristagaluh@utwente.nl
Indonesian Institute of Sciences, Indonesia
pesi001@lipi.go.id

L.J. Spreeuwers
Faculty of EEMCS
University of Twente, Netherlands
l.j.spreeuwers@utwente.nl

R.N.J. Veldhuis
Faculty of EEMCS
University of Twente, Netherlands
r.n.j.veldhuis@utwente.nl

***Abstract*—An important step in finger-vein recognition is a proper alignment of the finger vein patterns to be compared. This alignment method is used to handle finger pose variation and to enhance the stability of the finger vein authentication. We proposed the iterative closest point (ICP) method on finger contour for the alignment. After the aligning process we applied maximum curvature as a vein feature for the comparison without further optimization of the parameters, and we gained a better genuine comparison score. Even though this method is robust to finger pose variations, we have to further verify whether it will impact recognition performance. The experimental results show that the accuracy of proposed method in verification case is enhanced and increases slightly than the state-of-the-art registration method which is called center line registration. Using ICP for registration resulted in a reduction of the EER to 0.3% (from 0.7% for the center line registration) and a reduction of the FNMR@FMR0.01 to 0.7% (from 2.0% for the center line registration).**

***Index Terms*—biometrics, finger-vein pattern, ICP**

I. Introduction

Finger-vein recognition as a promising biometric technique has drawn increasing attention from the biometrics community in recent years. This method applies pattern-recognition techniques to images containing human finger vein patterns. During the last years, some research has shown several advantages, such as high-security level because the vein patterns are inside the human body [1], resistant to falsification because of the non-contact identification which uses physical information that cannot be verified visually [2] [3], low error rates, good spoofing resistant and a proper user convenience [4].

The vein pattern of a finger as a new method for the identification of individuals was proposed in 2000 by Kono et al. [5]. The later study in 2004, Miura et al. developed an authentication system using finger-vein pattern expressed in binary image [6] [3] and further research have been done to improve the result [2]. Some other studies used similar framework to extract finger-vein pattern which is composed of gradient normalization, principal curvature calculation, and binarization [7].

This research is funded by the Ministry of Research, Technology and Higher Education of the Republic of Indonesia and supported by the Indonesian Institute of Sciences (LIPI).

However, there are some problems in practice for finger-vein pattern as personal authentication. One of the problem is that the finger movements seems to be the cause of different finger placements and make the variations of vein patterns in the captured images [8]. Stated simply, the images were affected by position and orientation of the fingers. This could lead to the same fingers from different images not being well aligned, which posed a hindrance in recognition process. In order to suppress this effect, a proper alignment of finger-vein images is needed.

Although the aforementioned literatures investigated the effect of variance pose on finger-vein pattern recognition, alignment process is not being properly address that improper alignment might be able to affect to the performance. In this study, we propose a new alignment method in rigid registration that is Iterative Closest Point (ICP) based on finger contour of 2D images. This method is more advanced than the other study used in paper [1] [4]. Our results show an improvement to the recognition performance.

In this section, the overall work-flow of the paper is described. Section 2 includes related works. Section 3 draws brief description of methods regarding the proposed schemes. Section 4 shows the experiments, discussion and results of recognition using different methods in terms of Equal Error Rate (EER) and ROC curve. The statistic of genuine pairs is separately shown in the related tables. The dataset collection and parameter setup are also described in this section. Last comes the conclusion of the study in section 5. This is followed by some recommendations for the future works.

II. Related Works

Personal identification using finger-vein patterns has been popular in Biometrics research [1]− [7]. The state-of-the-arts on the finger-vein recognition, Miura et al. in 2004 developed a way of extracting global finger-vein patterns by iteratively tracking local lines or repeated line tracking from various starting positions to extract the patterns. Their study showed that extracting finger-vein patterns robustly to brightness fluctuations was possible with their method. They used 678 different finger images for identification and the accuracy was EER = 0.145% with a processing time of 0.5 seconds [3] [6].

The later study, in 2005 Miura et al. discovered that the repeated line tracking method could not extract the thin veins. Miura showed that the thickness of finger-vein pattern could differ due to varying amounts of bloods in the finger depending a certain conditions. For this reason, they developed a new method which calculated local maximum curvatures in cross-sectional profiles of a vein image and extracted the points with high curvature in each of four directions. This method also extracted the center lines of the veins consistently. Then they evaluated the robustness of the method against fluctuations in widths and brightnesses of veins. As a result, using the same dataset by the previous research (678 finger-vein images), the EER for personal identification was 0.0009% [2].

Misalignments caused by translations and rotations of the finger with respect to each axis occur when the finger was captured. Lee et al. [9] introduced alignment of a finger-vein images with extracted minutia points such as bifurcation and ending points of finger-vein regions. Their method used a simple affine transform based on a simple triangle which is composed of three minutia points of the finger vein region. Besides that, they also conducted a localizing the finger region with masking to normalize the finger vein image and extract the finger texture from the normalized image. Huang et al. [1] have been successfully to investigate the pose variations using pattern normalization model. This model based on a hypothesis that the fingers cross-sections are approximately ellipses and making the longitudinal axis in the middle of image. Also, it was called Center Line (CL) registration.

Another solution to displacement images was implemented in 2016 by Ma et al. [10] who reconstructed a 3D model of finger vein and used 3D point clouds matching of finger vein and contour to identify individuals. They used ICP to find transformation between two point sets through minimizing the sum square of the closest point pairs so that they can be matched. The first ICP algorithms was presented by Besl et al. [11]. This algorithms which is a procedure to find the closest point on a geometric entity to a given point, was implemented on 3-D shapes. ICP converges monotonically to the nearest local minimum of a mean-square distance metric.

III. Methods

Considering the problems above, a new scheme for personal identification based on finger-vein is proposed in this paper. Advanced affine transformations based on finger contour points was applied to overcome misalignments on captured images. Besides, verification performance will be compared with the state-of-the-arts scheme which was implemented by Ton et al. [4]. The process of both diagrams are illustrated in Fig. 1.

A. *Iterative Closest Point Based on Contour of Finger*

ICP is a straightforward method [11] to align two free-form shapes (model X, object P). Following describes each step in general:

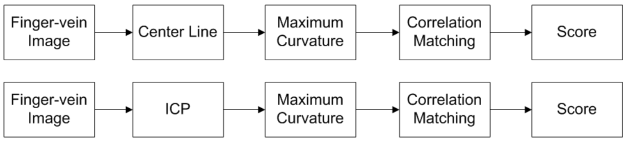

Fig. 1: Flowchart of the state-of-the-arts **upper** and the proposed scheme **lower** images.

- Initial transformation
- Iterative procedure to converge to local minima
  1) $\forall_p \in P$ find the closest $x \in P$
  2) $P_{k+1} \leftarrow Q(P_k)$ to minimize distances between each p and x
  3) Terminate when change in the error falls below a preset threshold or number of iterations are more than preset maximum number of iterations.
- Choose the best among found solutions for different initial positions

In this study, model and object are determined as finger contours. These contour points are drawn in Fig. 2 (a). Fixed point (green) is defined as the reference points. Another edge is moving point (red) which is defined as points which will be aligned to the fixed points. Also, the blue points as a registered contour is the results of applying a rigid registration of ICP on both contour points.

A comparison method for finger-vein images was implemented by further processing the image, followed by detection and registration of contour points, extract the feature and comparison them with existing method [2]. This scheme is shown in Fig. 1.

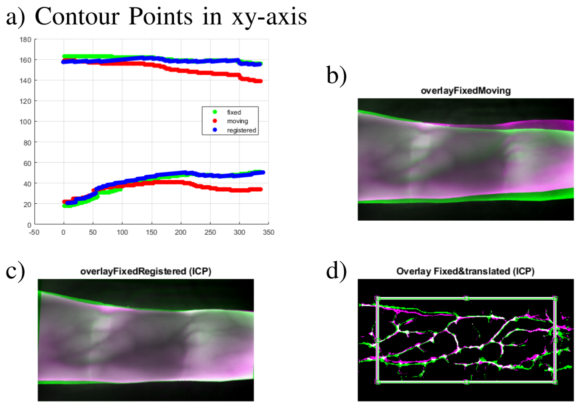

Fig. 2: Illustration of ICP based on contour of finger and feature extraction. The steps include **a** getting translation & rotation matrix from ICP, **b** Overlaid Fixed image (green) and moving image (purple), **c** Overlaid Fixed & Registered, **d** Overlaid Fixed & Registered of vein with sliding windows

The pipeline for this method was established in the following steps:

1) Extraction of finger contour was implemented by finger region mask, following the approach in [9]. Lee et al.

make assumption that the upper finger edge is present in the upper part of the image and the lower finger edge is present in the lower part of the image. The finger region is brighter than the background region. They localize the finger region to normalize the finger-vein and extract the contour from the normalized image. Furthermore, localizing finger region used masking method. Contour points have been drawn in Fig. 2 (a).

2) A maximum curvature method was used to perform finger-vein extraction, following in the paper [2]. Tuning parameters in this algorithm have been conducted to obtain a binary version of pattern comprising only the most reliable vein. The thresholds are determined experimentally by visual inspection. An example vein can be seen in Fig. 2 (d).
3) A vein pattern of moving image, which is purple color in Fig. 2 (b), was registered to fixed-vein image (green) by translation and rotation matrix resulting from ICP process in previous step. Thus, the overlay of registered vein patterns and fixed-vein image are shown in Fig. 2 (d). The overlaid also was performed to both original images, fixed and moving, in Fig. 2 (c).

B. Center Line Alignment

Center Line (CL) algorithm as the state-of-the-arts in alignment method was applied to compare the results of the ICP method. This model based on a hypothesis that the fingers cross-sections are approximately ellipses and the vein that can be imaged are near the finger surface. Huang et al. [1] describe the model as finger-vein pattern normalization model. This normalization assures that the finger will be aligned to the center of the image. And then, detected coordinates both edges (upper and lower), which are returned by the finger region detection, were used to approximate the longitudinal axis (midline/straight line) of the finger. Therefore, the parameters of this estimated line, rotations and translations, are used to create an affine image transformation. Ton et al. [4] also implemented this method to align the finger-vein image.

C. Vein Detection and Correlation Matching Score

In this study, the maximum curvature was used as a feature for matching two sets of binarised feature images which is described in paper by Miura et al [2]. This feature extraction method defined the location of maximum curvature from the image profile which are acquired in different position. Then, according to the rules as detailed in [2], all extracted points were connected and combined .

They also applied a sliding windows to calculate the correlation with optimum offset between two finger-vein pattern. This windows was defined as rectangular region with R(cw, ch) or R(x-offset, y-offset) and shown in Fig. 2 (d). Using the correlation formula, it was able to find where a section of an image fits in the whole without padding zeros around the image. As its mention in [3], the correlation N_m(s,t), which is the difference between the registered and input data at the

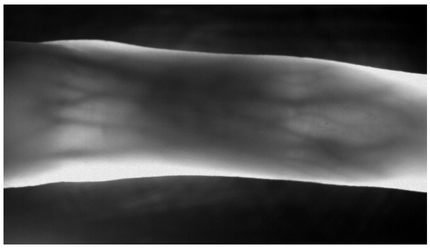

Fig. 3: Exemplary image from the database: vascular pattern of a left index finger.

positions where R(cw,ch) overlaps with I(s,t), is calculated as follows:

$$N_m(s,t) = \sum_{y=0}^{h-2c_h-1} \sum_{x=0}^{w-2c_w-1} I(s+x, t+y) R(c_w + x, c_h + y) \quad (1)$$

The maximum value of this correlation, $N_{m_{max}}$ matrix is normalised and used as matching score [3] [4].

IV. Experiments

In order to ascertain the performance improvement using the proposed schemes, we performed some experiments on public database. Besides, the goal of experiments is to examine whether the ICP make an impact on false reject on recognition or not.

A. Database and Setup

This research was based on a set of finger vascular pattern images acquired at the University of Twente, the Netherlands, in 2012 and was abbreviated as University of Twente Finger Vein Patterns (UTFVP) dataset. From each of the 60 subjects, vascular patterns of six fingers were captured - index, middle and ring finger of both hands. Images of each finger has been taken twice in each of two sessions. Thus, the total count of pictures in the set is 1440. The properties of images have 8-bit intensity images of resolution 672×380 pixels, with pixel density 126 ppcm [4]. An exemplary finger image is presented in Fig. 3.

In this experiment, we conducted a thorough setup to ensures the result consistently for both schemes. The parameters of sliding windows [2] was adjusted to the same value which is 30 pixels on parameter of c_w and c_h in Eq. 1. Its windows setting is greater than Ton et al. [4] did. Additionally, the experiment used codes of function to extract and match the finger-vein images which is provided by Ton et al. [4].

B. Correlation-based Matching

In addition to the aforementioned methods, the normalized correlation in metric between images was also studied as an identification or a verification metric. The method has been explained and used in e.g. [4], making it a good comparative method to quantify the possibility to identify a person solely on the basis of finger-vein pattern.

Here, the comparison between the proposed ICP framework and the state-of-the-arts is conducted to UTFVP dataset. Three benchmarks of both methods are given in Table I. The table shows that the rigid registration by ICP has better performance than the center line. The ICP can reduce a half performance of center line's EER, and it is also shown by Receiver Operating Characteristic (ROC) curve in Fig. 4. Furthermore, it also can be seen from the table that the significant improvement on reducing False Non Match Rate (FNMR) is achieved by the proposed method.

TABLE I: Comparison of Registration Methods

Method	EER (%)	FNMR@FMR0.01 (%)	AUC
ICP	0.32	0.69	0.9995
CL	0.69	2.04	0.9990

In other words, ICP gives slightly a contribution to robustness on misalignment images, especially in case of translation and rotation in plane. Fig. 4 illustrates that false rejection of the genuine images by ICP method decreased drastically compare to CL, which is also shown by Area Under Curve (AUC), and making the similarity of the genuine increased.

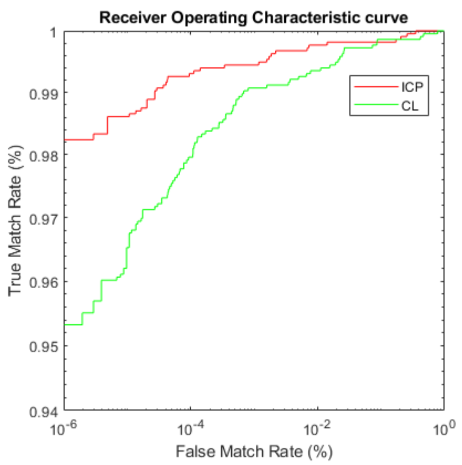

Fig. 4: ROC curve of both methods

C. Genuine Scores

In order to investigate large variations of genuine pairs, distribution of genuine has been defined. Mean of the optimal translation on x-axis (s_0) and y-axis (t_0) based Equation in paper [3] was calculated, and it is described in Table II. However, although these means have the same value, but the similarity score between genuine pairs both methods is different as it was shown in ROC curve in Fig. 4.

The table also shows the mean and maximum distance (d) which is determined for both methods (ICP and CL) by following formula:

$$d = \sqrt{(s_0 - s_{0_{mean}})^2 + (t_0 - t_{0_{mean}})^2}$$

TABLE II: Statistic of Genuine Pairs

Registration Method	Mean of parameter			Max of distance (d)
	s_0	t_0	d	
ICP	32.6	31.2	5.5	31.6
CL	32.5	31.2	6.0	32.6

s_0,t_0 : x,y-optimum displacement in correlation matching

Even though the mean and maximum of distance (d) by ICP are a little bit different, but the distance draw solely the position of the varied genuine outliers based on the optimum translation parameters in Eq. 1.

D. Discussion

The experimental results, which is in verification scenario, achieve significant improvement in the performance e.g 0.32% improvement in EER and 0.69% for FNMR@FMR0.01%. This result used large sliding windows (rectangular region) to define the correlation between two finger-vein pattern images. However, in this experiments, we also performed different setting on the sliding windows parameter. In fact, our objective in these experiments is to ensure the impact of a proper alignment to the performance. When ICP based on finger contour give a proper alignment, the needed size of sliding windows should be small and therefore, the optimum offset of correlation will have the same position with the sliding windows of the template. Although, the ICP is able to overcome the problem of misalignment, but the score of correlation relies on the vein patterns itself.

V. Conclusion

This paper proposes a registration method based on contour points of finger-vein images. The experimental results show that the proposed method outperforms the state-of-the-arts. Furthermore, the most important outcome is that the ICP is able to solve translation and internal rotation displacement. It was shown by the performance that EER was 0.32% and FNMR@FMR0.01 was 0.69%. That is, the proposed method can increase the similarity of the genuine images, and further, decline the false rejection in recognition.

In future, combination between contour and vein pattern itself can be used as base on the alignment process. Further optimization of the parameters on feature extraction method and ICP are needed to get better performance.

References

[1] B. Huang, Y. Dai, R. Li, D. Tang, and W. Li, "Finger-vein authentication based on wide line detector and pattern normalization," in *2010 20th International Conference on Pattern Recognition*. IEEE, 2010, pp. 1269–1272.

[2] N. Miura, A. Nagasaka, and T. Miyatake, "Extraction of finger-vein patterns using maximum curvature points in image profiles," *In IAPR conference on Machine Vision and Applications*, no. 9, pp. 347–350, may 2005.

[3] ——, "Feature extraction of finger vein patterns based on iterative line tracking and its application to personal identification," *Systems and Computers in Japan*, vol. 35, no. 7, pp. 61–71, 2004.

[4] B. Ton and R. Veldhuis, "A high quality finger vascular pattern dataset collected using a custom designed capturing device," 2013.

[5] M. Kono, "A new method for the identification of individuals by using of vein pattern matching of a finger," in *Proc. Fifth Symposium on Pattern Measurement, Yamaguchi, Japan, 2000*, 2000, pp. 9–12.

[6] N. Miura, A. Nagasaka, and T. Miyatake, "Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification," *Machine Vision and Applications*, vol. 15, no. 4, pp. 194–203, 2004.

[7] J. H. Choi, W. Song, T. Kim, S.-R. Lee, and H. C. Kim, "Finger vein extraction using gradient normalization and principal curvature," in *Image Processing: Machine Vision Applications II*, vol. 7251. International Society for Optics and Photonics, 2009, p. 725111.

[8] Q. Chen, L. Yang, G. Yang, Y. Yin, and X. Meng, "Dfvr: Deformable finger vein recognition," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2017, pp. 1278–1282.

[9] E. C. Lee, H. C. Lee, and K. R. Park, "Finger vein recognition using minutia-based alignment and local binary pattern-based feature extraction," *International Journal of Imaging Systems and Technology*, vol. 19, no. 3, pp. 179–186, 2009.

[10] Z. Ma, L. Fang, J. Duan, S. Xie, and Z. Wang, "Personal identification based on finger vein and contour point clouds matching," in *2016 IEEE International Conference on Mechatronics and Automation*. IEEE, 2016, pp. 1983–1988.

[11] P. J. Besl and N. D. McKay, "Method for registration of 3-d shapes," in *Sensor Fusion IV: Control Paradigms and Data Structures*, vol. 1611. International Society for Optics and Photonics, 1992, pp. 586–607.