New Finger-vein Recognition Method Based on Image Quality Assessment

Dat Tien Nguyen[1], Young Ho Park[1], Kwang Yong Shin[1], and Kang Ryoung Park[2*]
[1]*Member*, Division of Electronics and Electrical Engineering, Dongguk University, 26, Pil-dong 3-ga, Jung-gu, Seoul 100-715, Republic of Korea
[e-mail: datdtbkhn.nguyen@gmail.com]
[e-mail: fdsarew@hanafos.com]
[e-mail: skyandla@dgu.edu]
[2]*Member*, Division of Electronics and Electrical Engineering, Dongguk University, 26, Pil-dong 3-ga, Jung-gu, Seoul 100-715, Republic of Korea
[e-mail: parkgr@dgu.edu]
*Corresponding author: Kang Ryoung Park

Received November 27, 2012; revised January 23, 2013; accepted February 13, 2013; published February 26, 2013

Abstract

The performance of finger-vein recognition methods is limited by camera optical defocusing, the light-scattering effect of skin, and individual variations in the skin depth, density, and thickness of vascular patterns. Consequently, all of these factors may affect the image quality, but few studies have conducted quality assessments of finger-vein images. Therefore, we developed a new finger-vein recognition method based on image quality assessment. This research is novel compared with previous methods in four respects. First, the vertical cross-sectional profiles are extracted to detect the approximate positions of vein regions in a given finger-vein image. Second, the accurate positions of the vein regions are detected by checking the depth of the vein's profile using various depth thresholds. Third, the quality of the finger-vein image is measured by using the number of detected vein points in relation to the depth thresholds, which allows individual variations of vein density to be considered for quality assessment. Fourth, by assessing the quality of input finger-vein images, inferior-quality images are not used for recognition, thereby enhancing the accuracy of finger-vein recognition. Experiments confirmed that the performance of finger-vein recognition systems that incorporated the proposed quality assessment method was superior to that of previous methods.

Keywords: Biometrics, finger vein recognition, quality assessment

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (No. 2012R1A1A2038666), and in part by the Public welfare & Safety research program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (No. 2012-0006554).

http://dx.doi.org/10.3837/tiis.2013.02.010

1. Introduction

Biometrics such as the recognition of the face, fingerprint, voice, iris, and finger-vein have been used frequently in various fields, such as door access controls, internet banking, personal identification for computer access, automated teller machines (ATMs), and border control checks [1][2]. Finger-vein recognition uniquely identifies individuals based on the vascular patterns inside their fingers. This method has the advantages of compact device size, high accuracy, and user convenience; however, its current implementations can be affected by various factors [3][4] such as changes in the temperature and physical conditions when capturing images, non-uniform near-infrared (NIR) light, and variations in the finger thickness. In addition, the simple structure or sparse density of vein line patterns, optical defocusing, and blurring caused by the scattering of NIR light on the skin surface also affect the performance of finger-vein recognition. Previous research on the quality of biometrics can be divided into two categories: quality assessment and quality enhancement of biometric data. In fingerprint recognition, the quality of the fingerprint image is measured [5][6] or enhanced [7][8][9][10][11]. In face recognition, variations in illumination are considered to ensure the quality of the results [12][13]. In the field of finger-vein recognition, however, most previous studies have focused on enhancing the quality of the image. Yang et al. proposed a method based on multichannel Gabor filtering for enhancing finger-vein images [14]. Zhang et al. integrated circular Gabor filtering and the gray-level grouping method to enhance the image quality [15]. Using the gray-level grouping method, the finger-vein image was initially enhanced in terms of image contrast. The image quality of the vein lines was then enhanced using the circular Gabor filter. Yang et al. combined directional decomposition and Frangi filtering to improve the quality of the vein pattern in finger-vein images [16]. In a previous study, Yang et al. proposed a method for scattering removal for improving the quality of a finger-vein image, which could improve the image contrast [17]. Yang et al. also proposed a method for enhancing the quality of finger-vein images using an orientation field, which was based on variations of the coarse vein width and transforms of line- and curve-filters [18]. In previous studies, the quality of hand-vein images was measured using two indicators based on the mean and variance of gray levels [19][20]. These indicators only considered the average brightness and variance of the input images, and the final quality score could still be high even if the image was too bright or the variance of the image was too high due to excessive noise. The bifurcation and ending points of vein lines could be detected as minutiae points, and the finger-vein image quality was assessed based on the minutiae detected [21]. This quality measure was based on a limited number of minutiae points, so the errors when detecting minutiae points could affect the performance of the quality measurement. Hartung et al. presented a quality measurement method for vein images based on features of the global and local characteristics, which used the gray level co-occurrence matrix (GLCM) and metadata [22]. As shown in [23][24][25], ISO/IEC 29794:2009 includes ISO standards for the framework, finger image, face, and iris. In standard finger images, only the quality contents of the fingerprint are included. Thus, ISO/IEC 29794:2009 does not contain any quality contents related to vein images (e.g., finger-vein, palm-vein, and hand-vein).

Given the problems of previous studies, we propose a new method for finger-vein recognition, which is based on a quality assessment of finger-vein images using the vein points detected on the vein lines instead of the minutiae points. The proposed method extracts the vertical cross-sectional profiles to determine the approximate positions of the vein regions in a given finger-vein image. Then, the proposed method accurately detects the positions of the vein regions by checking the depth of the vein profile using various depth thresholds. Based on the detected positions, the proposed method measures the quality of the finger-vein image using the number of detected vein points (NDVP) relative to the depth thresholds, which allows individual variations in the vein density to be considered for quality assessments. In this study, the vein points are all the image pixel points on the detected vein lines. Finally, the proposed method assesses the quality of input finger-vein images and images of inferior quality are not used for recognition, thereby enhancing the accuracy of finger-vein recognition. **Table 1** compares previous vein image's quality assessment methods and our proposed method. The organization of this paper is as follows. Section 2 describes our proposed quality-based finger-vein recognition method. Sections 3 and 4 present the experimental results and conclusions, respectively.

Table 1. Comparisons of the quality assessment methods of vein image

Appearance-based method		Method	- The quality of the vein image is measured using two indicators, which are based on the mean and variance of the gray levels [19][20].
		Advantage	- Easy to implement. - Short processing time.
		Disadvantage	- The final quality score can be high even if the image is too bright or the variance of the image is too high due to excessive noise.
Shape-based methods	Minutiae-based method	Method	- The bifurcations and ending points of vein lines are detected as minutiae points. The finger-vein image quality is assessed based on the minutiae detected [21].
		Advantage	- The quality assessment method considers that finger-vein recognition is successful because vein minutiae points can be used for recognition.
		Disadvantage	- The quality measure is based on a limited number of minutiae points, so errors when detecting minutiae points can affect the quality measurement performance.
	Vein-point based method (Proposed method)	Method	- The quality is measured using the detected vein points on the vein lines.
		Advantage	- The quality is measured using the detected vein points on the vein lines instead of minutiae points, so the quality assessment performance is not affected by the detection of a limited number of minutiae points. - Images with a higher quality determined using the proposed quality assessment can improve the results and lead to successful recognition. This is because images of good and poor quality, which are used during training in our quality assessment method, are determined based on the finger-vein recognition results, i.e., they are not determined manually.
		Disadvantage	- The performance when detecting vein areas may affect the quality assessment performance.

2. Proposed Quality-based Finger-Vein Recognition Method

2.1 Overall Procedure of the Proposed Method

Fig. 1 outlines the flowchart of the proposed method. The proposed system comprises the finger-vein quality (FVQ) assessment method and the finger-vein recognition method. The FVQ assessment is performed using the captured finger-vein image (see details in section 2.2 and **Fig. 2**). If the calculated quality scores of the input and enrolled finger-vein images are greater than the predetermined threshold at the same time, the captured image is used for recognition (see details in section 2.3 and **Fig. 10**). If this is not the case, there is no attempt at recognition, which can enhance the performance of the finger-vein recognition system.

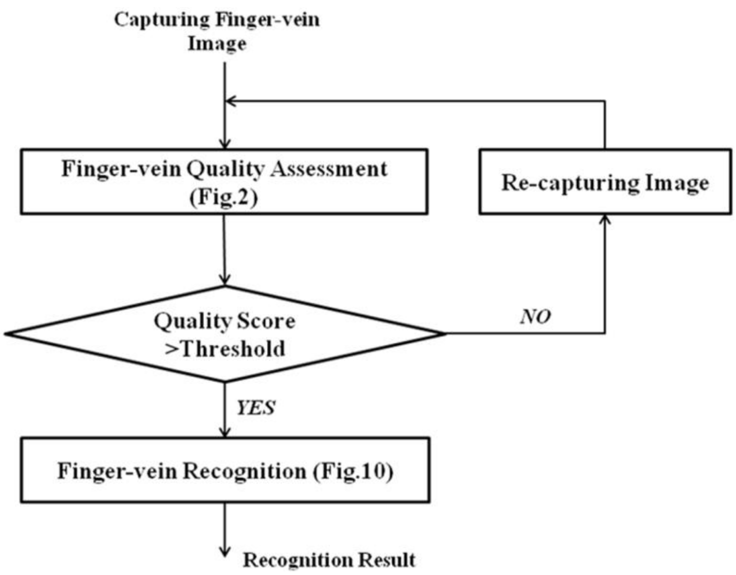


Fig. 1. Overall procedure of the proposed method

2.2 Quality assessment of finger-vein images

Capturing a clear vein pattern in the finger-vein image is crucial in finger-vein recognition. **Fig. 2** shows the proposed algorithm used for finger-vein image quality assessment.

We considered the following two aspects when assessing the quality of finger-vein images:

- Differences in the depth of the vein line in good and poor quality finger-vein images.
- The complexity of the vein line structure in the vein patterns of the finger.

These two aspects were assessed using the NDVP for a given finger-vein image at various depth thresholds, as outlined in **Fig. 2**. **Fig. 3** shows an example of the differences in the depth of the vein line in good- and poor-quality finger-vein images. In **Fig. 3**, Image 2 is more blurred than Image 1, although both images were captured from same finger. The right side of **Fig. 3** shows the gray profiles of the vein line in the vertical direction at the same position (A) on the finger. The gray profile of Image 1 is deeper than that of Image 2. This example shows that the depth of the vein line is an important factor that affects the quality of a finger-vein image. Another factor that may affect the accuracy of finger-vein recognition is the complexity of the vein line structure in a vein pattern, as shown in **Fig. 4**. Therefore, these two factors (the depth of the vein line and the complexity of the vein line structure of a vein pattern) are used for measuring the quality of finger-vein images using NDVP, as follows.

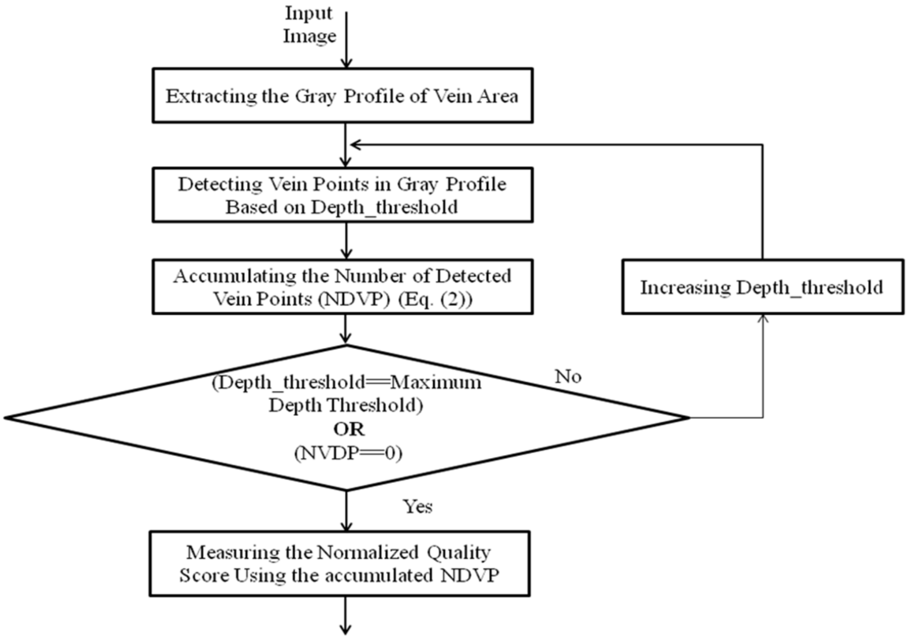


Fig. 2. The procedure used by the proposed finger-vein quality assessment method.

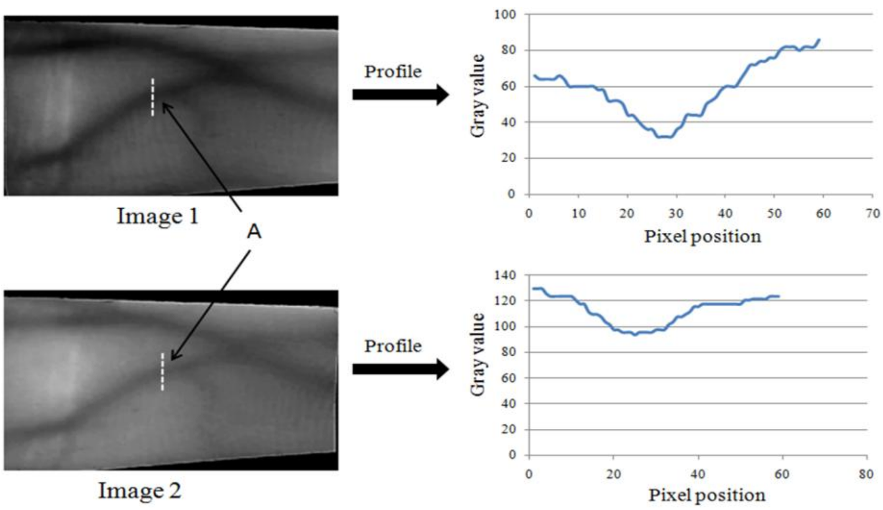
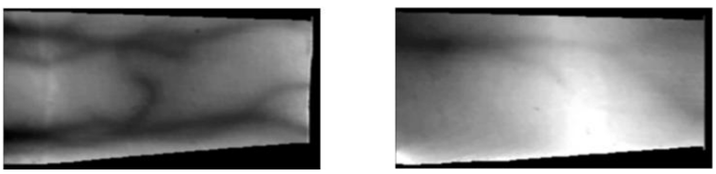


Fig. 3. Examples of the differences between a good-quality image (Image 1) and a poor-quality image (Image 2) of the finger-vein in terms of the valley depth in the cross-sectional profile of the vein line (position A)



(a) (b)

Fig. 4. Examples of good- and poor-quality images: (a) good-quality and (b) poor-quality finger-vein images in terms of the complexity of the vein line patterns

As explained above, the vein points in the good-quality images have higher depth values compared with the poor-quality images, which means that the difference in quality between the images can be measured by comparing the depth values. First, all the candidate vein points are detected in finger-vein image. Then, the depth values are calculated for each candidate vein point. After comparing the depth value (the value b of **Fig. 8**) of each candidate vein point with a depth threshold, as shown in **Fig. 2**, a candidate vein point with a lower depth value is removed, whereas a candidate vein point with a higher depth value is retained. After changing the depth threshold from low to high, the detected vein points in good-quality images tend to be maintained because their depth values are high. However, the points in poor-quality images have a tendency to be removed because of their low depth values. Thus, after iterating through several changes in the depth threshold of **Fig. 2**, the number of candidate vein points in poor-quality images is low, whereas the number of candidate vein points in good-quality images remains high. Consequently, the NDVP of the good-quality image is higher than that of the poor-quality image. We confirmed that a higher NDVP correlated with higher depth values for the vein points. The recognition accuracy of the image with the high complexity of vein line patterns (**Fig. 4 (a)**) was usually higher than that with a low complexity of vein line patterns (**Fig. 4 (b)**). Thus, an image with more complex patterns of vein lines may be regarded as a good-quality image. Since the NDVP of the image (**Fig. 4 (a)**) is higher than that of the image (**Fig. 4 (b)**) with the same depth threshold, we can know that the NDVP also represents the complexity of vein line patterns of the images. In detail, a higher NDVP in an image correlated with a higher complexity of vein line patterns. **Fig. 5** shows an example of the change in NDVP depending on the threshold in the images shown in **Fig. 4**. The NDVP of Image 1 (**Fig. 4 (a)** with more complex vein line patterns) was higher than that of Image 2 (**Fig. 4 (b)** with less complex vein line patterns) for all depth thresholds. This confirms that the NDVP indicates the complexity of vein line patterns in an image. As shown in **Fig. 2**, three main steps were used to assess the quality of a finger-vein image, as follows:

- Extract the gray profile of the vein region
- Detect the vein points in the gray profiles based on the depth threshold
- Accumulate the NDVP and measure the normalized quality score based on the accumulated NDVP

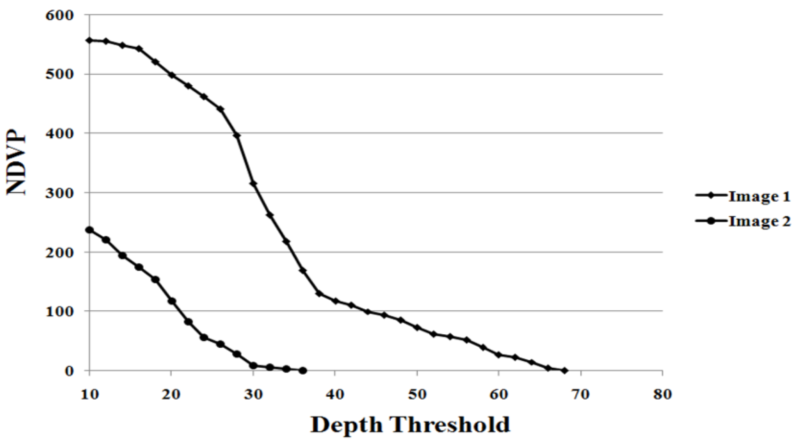
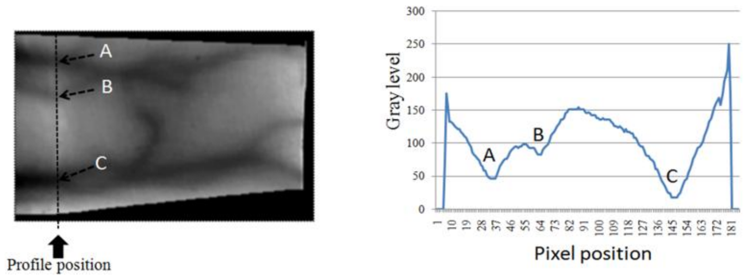


Fig. 5. Changes in the NDVP of Image 1 (good-quality image) and Image 2 (poor-quality image) depending on the depth threshold (**Fig. 2**)

2.2.1 Extracting the Gray Profile of a Vein Region

The hemoglobin in a vein absorbs NIR light better than the skin on the finger, so the vein lines appear to be darker than the skin, as shown in **Fig. 6 (a)** [26]. Based on this property, the vein lines can be detected by identifying the darker points in the finger-vein image. Our algorithm uses the cross-sectional profile [3] to identify the vein points. In **Fig. 6 (b)**, the vein point and its neighbors are shown as localized curves in the gray profile and these characteristics can be used to detect the vein points. The first step in our algorithm is to extract the gray profiles from the input image. Most of the vein lines are distributed along the finger (the horizontal direction as shown in **Fig. 6 (a)**), so our algorithm only considers the gray profiles in the vertical direction. **Fig. 6** shows an example of a finger-vein image and its gray profile in the vertical direction. The finger-vein image is usually obtained when users touch their finger on the device. Hence, the distance from the camera to the finger is approximately the same, and the sizes of the finger regions and their cross-sectional gray-level profiles vary only slightly. In addition, NIR light illumination and a camera without visible light are used for acquiring the images with distinctive vein patterns. Therefore, illumination variations due to external visible light are not present in the image. However, the orientation of the finger and the illumination variation caused by variations in the finger thickness and the presence of bone or skin can affect the cross-sectional gray-level profiles. In future, we intend to develop a method for extracting the cross-sectional gray-level profiles, which will be robust to variations in orientation and illumination.



(a) (b)

Fig. 6. Example of a gray profile of a finger vein image: (a) finger vein image and (b) its gray profile

2.2.2 Detecting Vein Points in the Gray Profile based on the Depth Threshold

To detect the vein point, we first calculate the gradient vector of the gray profile. The gray profile of a vein looks like a concave curve, which causes the gradient sign to change across the vein point, as shown in **Fig. 6**. As shown in **Table 2**, the positive and negative gradient values have a gradient sign of +1 and -1, respectively. The candidate vein point is determined at the position where the gradient sign changes from -1 to +1. We can also extract the leftmost and the rightmost positions of the profile of each vein point by checking the change of gradient sign from +1 to -1. **Fig. 7** shows a visualization of the curve in **Table 2**.

Table 2. Change in the gradient sign along the gray profile of the vein area

Gray level	42	45	48	37	27	20	15	18	24	37	48	45	40
Gradient sign	+	+	+	-	-	-	-	+	+	+	+	-	-
Position			Leftmost position				Candidate vein position				Rightmost position		

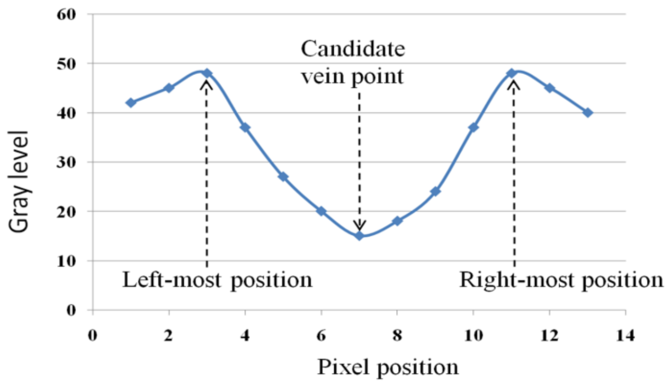


Fig. 7. Visualization of the gray profile in the vein area (**Table 2**)

Spurious vein points may be detected due to image noise, so it is necessary to decide whether a candidate vein point is correct. **Fig. 8** shows how the depth of the vein curve is calculated for each candidate vein point.

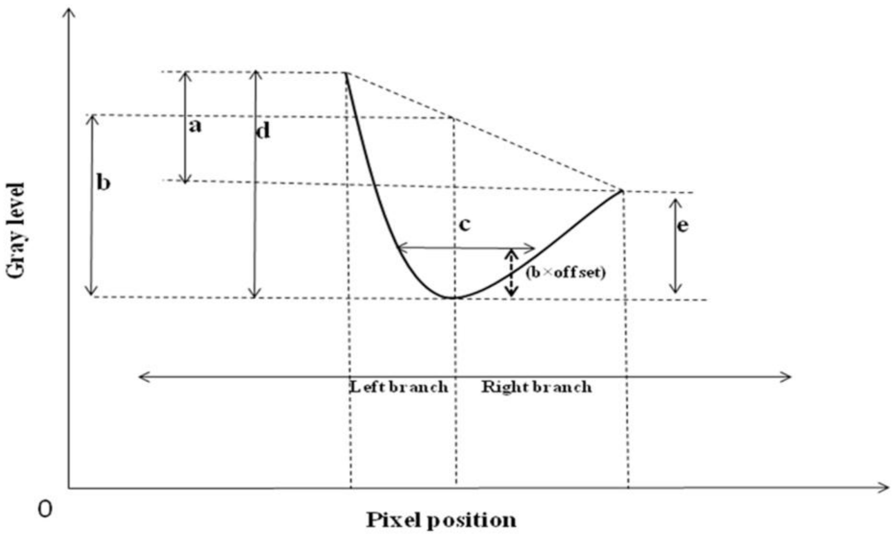


Fig. 8. Vein profile and its depth calculation

A curve is considered to be a vein line if the following conditions are satisfied:

if ((b ≥ (a × dif_threshold)) *AND* (b ≥ depth_threshold) *AND* (c ≥ width_threshold))
then (The points of the curve belong to a vein line)
else (The points of the curve do not belong to a vein line) (1)

Where a is |d – e| and b is the depth of the curve, calculated as (d + e)/2. c is determined at the position where the depth is b × offset as shown in **Fig. 8**. The optimal offset is determined by considering the size of the vein line and the resolution of finger vein image, which are not database-dependent. In the experiments presented in section 3, we used the same offsets in all tests with “Database 1” and “Database 2.” The value d is the gray-level difference between the leftmost position and the candidate vein point, and e is the gray-level difference between the rightmost position and the candidate vein point. The optimal values for dif_threshold and width_threshold are determined experimentally. dif_threshold is used to ensure the balance between the two branches of a curve. Because noise components always appear in the image, width_threshold is used to prevent any spurious points caused by the noise from being incorrectly determined as vein points. depth_threshold is determined based on the starting and ending positions of the depth threshold. In the example shown in **Fig. 5**, the starting position of the depth threshold is maintained at 10 in all the input images. However, the ending position of the depth threshold is changed depending on the image. Specifically, the ending position is determined as the point where NDVP becomes 0. A curve is considered to be a vein line when the conditions of Eq. 1 are satisfied, and the minimum point of the gray level of this curve (which satisfies the conditions in **Table 2** and **Fig. 7**) is determined as the vein point at the current depth_threshold (depth_threshold of **Fig. 2**).

2.2.3 Accumulating the NDVP and measuring the normalized quality score based on the accumulated NDVP

As explained earlier, the depth of vein line and the complexity of the vein line structure are used to assess the quality of finger-vein images in this method, which are calculated based on the NDVP. A good-quality image has a higher depth value in the gray level of the vein line and a more complex structure in the vein line pattern than a poor-quality image, so the NDVP of a good-quality image is less affected by the depth threshold compared with a poor-quality image. Thus, the NDVP of a good-quality image (according to depth threshold in **Fig. 2**) is higher than that of a poor-quality image, as shown in **Fig. 5**. Therefore, the size of the area defined by the depth threshold versus the NDVP of good-quality images is higher than that of poor-quality images, as shown in **Fig. 5** and **Fig. 9**.
Based on the NDVP values, the FVQ is calculated as

$$FVQ = \sum_{i=a}^{b} NDVP_i \tag{2}$$

Where a and b are the minimum and maximum depth thresholds. Based on the entire dataset, including the learning and testing databases, the FVQ is normalized using the Min-Max rule [27] and it ranges from 0 to 1, where 1 indicates the highest-quality image, and 0, the lowest. As shown in **Fig. 1**, finger-vein recognition is performed using the input image. If the calculated FVQ is not greater than the threshold, finger-vein recognition is not attempted. The optimal threshold is determined experimentally using the learning database (genuine test); hence, the minimum equal error rate (EER) for discriminating good- and poor-quality images is obtained. The reasons for using the learning database (genuine test) are provided at the end of section 2.2.3. The EER was calculated for the case when the false rejection rate (FRR) was the same as the false acceptance rate (FAR) [26]. The FAR indicates the error rate of falsely accepting a poor-quality image as a good-quality one. The FRR is that of falsely rejecting a good-quality image as a poor-quality one. The aim of the proposed quality assessment method is to improve the finger-vein recognition accuracy; hence, the ground-truth good- and poor-quality images are identified using the finger-vein recognition result (genuine comparison). That is, if a finger-vein image is correctly recognized in a genuine comparison, it is determined to be a good-quality image. If a finger-vein image is not recognized correctly in the genuine comparison, it is determined to be a poor-quality image. In the case of imposter comparisons, two images cannot be recognized because they are imposter images (finger-vein images from different fingers), rather than poor-quality images. Therefore, the identification of good- and poor-quality images cannot be achieved using imposter comparisons.

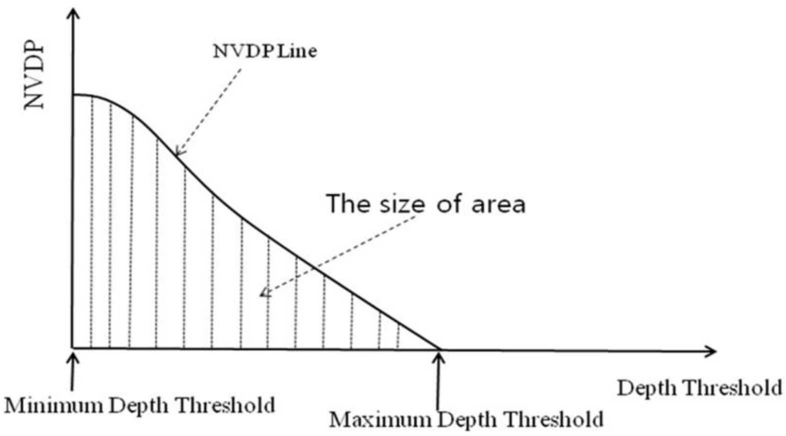


Fig. 9. Quality measurement of a finger-vein image, where the area is defined by the depth threshold in **Fig. 2**, versus NDVP

2.3 Finger-vein recognition

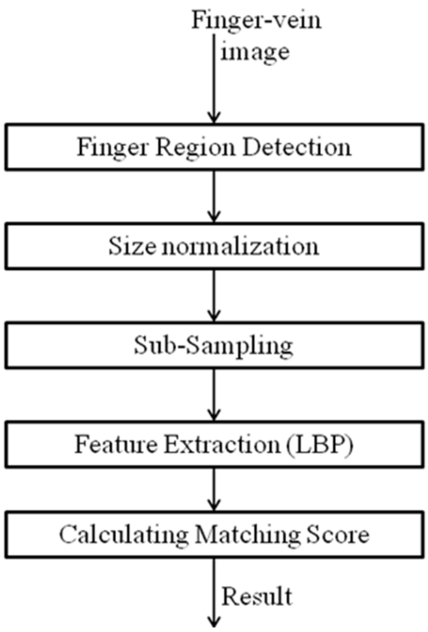


Fig. 10. Finger-vein recognition algorithm based on textural information using LBP [26]

Fig. 10 shows the primary procedure used for finger-vein recognition, which is explained in detail as follows [26]. Using the input image (where the quality score, i.e., the FVQ derived using Eq. 2, is greater than the threshold), the finger region is detected using masks that separate the finger region from the background of the finger-vein image. The size-normalization step stretches the detected finger region into a rectangular shape measuring 150 × 60 pixels. To reduce the processing time of the finger-vein code extraction and matching steps, sub-sampling step is performed to produce a sub-sampled image of 50 × 20 pixels by calculating the average gray level in each 3 × 3 pixel block [26]. The finger-vein code is then extracted from the sub-sampled image using the local binary pattern (LBP) method. Using the finger-vein code, the matching score is calculated based on the Hamming distance [26].

3. Experimental Results

To measure the performance of the proposed method of finger-vein quality assessment, we used a database containing 3,300 finger-vein images of 10 fingers from 33 people (10 images per finger). All the images in the database were captured using an in-house device at a time interval and the image resolution was 640 × 480 pixels with an 8-bit gray level [26]. We referred to this database as "Database 1." **Fig. 11** shows examples of images in "Database 1," where the FVQs were calculated using Eq. 2, and the hamming distances (HDs) of finger-vein recognition. The HD was calculated by finger-vein recognition using the two images in the first and second rows. As shown in **Fig. 11**, a higher FVQ correlated with a lower HD. "Database 1" was divided randomly into learning and testing databases. The learning database contained data from 17 people, whereas the data from the remaining 16 people were used for the testing database. This procedure was iterated four times for calculating the average accuracy of the finger-vein recognition method.

The learning database of 17 people was only used to identify the optimal threshold for FVQ. During testing, the finger-vein images of only 16 people were used for enrollment and recognition (i.e., it did not use the images from the other 17 people). This is a common cross-validation method used to measure the performance of biometric systems.

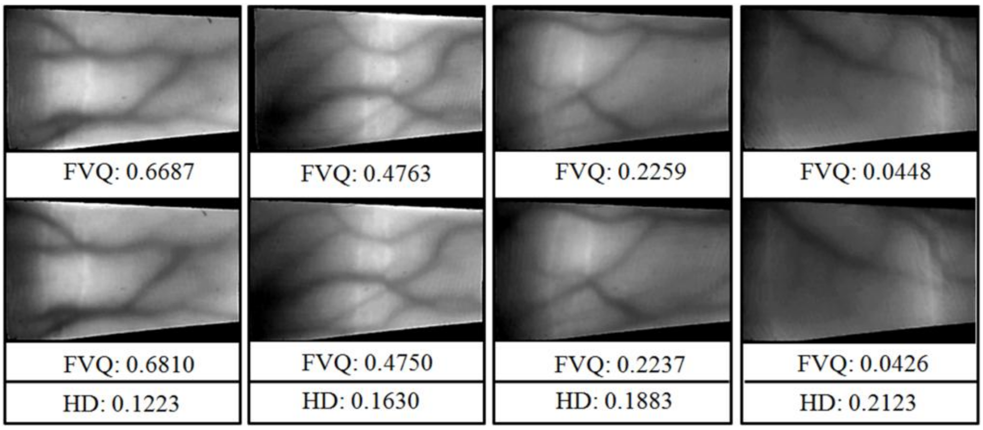


Fig. 11. Examples from "Database 1," showing the calculated quality scores (FVQ using Eq. 2) and HDs of finger-vein recognition (two finger-vein images of the same finger).

In general, the quality of the enrolled and input finger-vein images should be considered to ensure good accuracy finger-vein recognition. Even if the quality of the enrolled images is good, recognition can fail if the quality of the input images is poor and vice versa. Therefore, we compared the accuracies of the two schemes using SUM and AND rules to consider the quality scores (FVQ using Eq. 2) of the enrolled and input finger-vein images. For the SUM rules, if the sum of the quality scores of the enrolled and input finger-vein images was greater than the threshold, an attempt was made to match the input image with the enrolled image. If the sum of the quality scores of the enrolled and input finger-vein images was not greater than the threshold, the input image was not matched with the enrolled one. In **Fig. 1**, the "Quality Score" is the summed quality scores of the enrolled and input finger-vein images for the SUM rule. For the AND rules, an attempt was made to match the input image with the enrolled one if the quality score of the enrolled image exceeded the threshold and the input image was also greater than the threshold at the same time. If the quality score of the enrolled image was not greater than the threshold (even in the case where one of the two quality scores was not greater than the threshold), the input image was not matched with the enrolled one. In Fig. 1, "Quality Score > Threshold" applies when the quality score of the enrolled image exceeded the threshold and the input image was also greater than the threshold in the case of the AND rules.

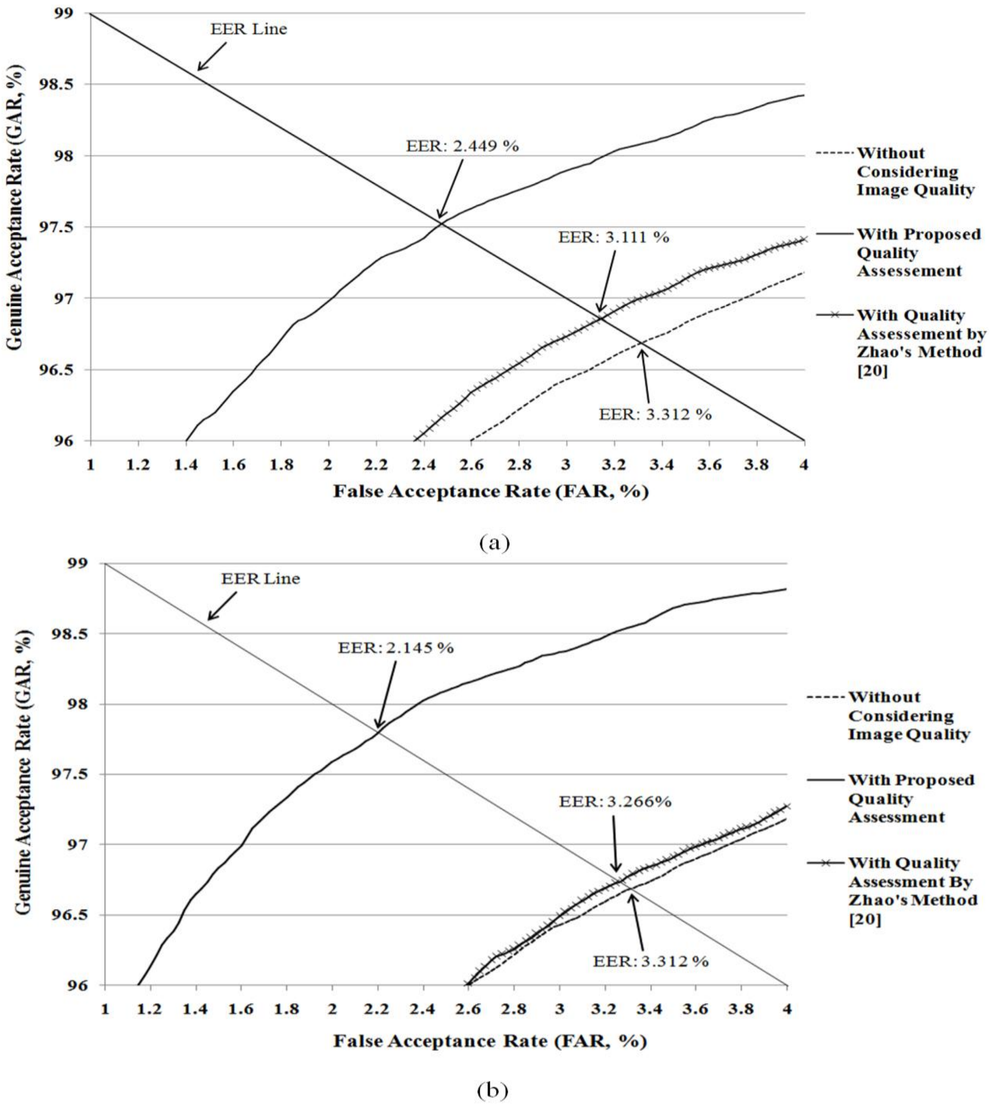


Fig. 12. Average ROC curves with and without the proposed method, and the previous method (using "Database 1"): (a) based on the SUM rules and (b) based on the AND rules

First, we compared the performance of our method with another quality assessment method [20]. **Fig. 12** shows the average receiver operating characteristic (ROC) curves for finger-vein recognition without the proposed method ("Without Considering Image Quality" in **Fig. 12**), with the proposed method ("With Proposed Quality Assessment" in **Fig. 12**), and with Zhao's method [20]. For comparison, the accuracy of the proposed quality assessment method was compared with that of Zhao's method [20]. In Zhao's method [20], the quality of vein images was measured using two indicators based on the mean and variance of gray levels. To ensure a fair comparison, the same finger-vein recognition method (based on the LBP in Section 2.3) was used with same database ("Database 1") in our experiments.

Fig. 12 (a) and **Fig. 12 (b)** show the results with the SUM rules and the AND rules, respectively. In **Fig. 12**, the genuine acceptance rate (GAR) is 100 – FRR (%) [26]. As shown in **Fig. 12**, the accuracy with the proposed quality assessment method exceeded that without the proposed quality assessment method and Zhao's method [20]. Here, the EER was calculated for the case when the false rejection rate (FRR) was the same as the false acceptance rate (FAR) [26]. The FAR indicates the error rate of falsely authenticating unregistered person as registered one. The FRR is that of falsely rejecting a registered person as an unregistered one [26].

In the next experiment, we performed tests using another database. We referred to this database as "Database 2." "Database 1" was captured at time intervals, so the misalignments of images in "Database 1" were greater than those of "Database 2," (which were collected without a time interval) [26]. Originally, "Database 2" contained 900 finger-vein images from 12 people. Based on the 900 original finger-vein images, "Database 2" was expanded to 3,600 finger-vein images by including blurred images based on Gaussian filtering to address the problem of the small numbers in the database and also to test the blurring effect during quality assessments. Because of the blurring, the high-frequency components in the original finger-vein images were reduced and the quality of the images was degraded. **Fig. 13** shows some images from "Database 2," their quality scores measured using the proposed quality assessment method, and the calculated HDs of finger-vein recognition. As shown in **Fig. 13**, a higher FVQ was correlated with a lower HD.

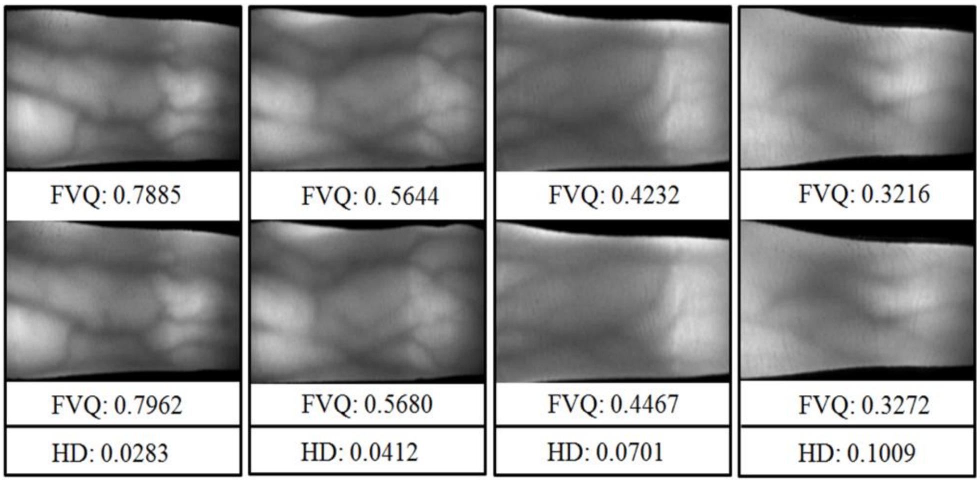


Fig. 13. Examples from "Database 2," calculated quality scores (FVQ of Eq. 2), and HDs of finger-vein recognition (with two finger-vein images from same finger)

Similar to **Fig. 12**, the average ROC curves of finger-vein recognition without the proposed method and those with the proposed method were obtained, as shown in **Fig. 14**. **Fig. 14** shows the results with the SUM rules and the AND rules. In **Fig. 14**, the accuracy with the proposed method of quality assessment exceeded that without the proposed quality assessment method. **Fig. 12** and **Fig. 14** also confirmed that finger-vein recognition with the proposed quality assessment method gave a higher accuracy, irrespective of the type of database used.

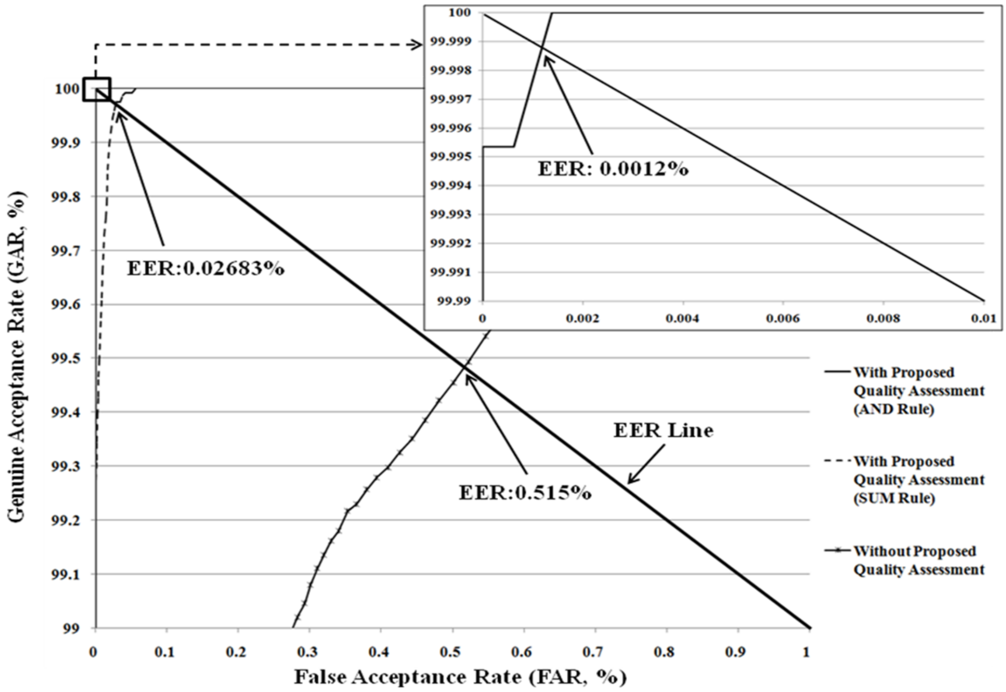
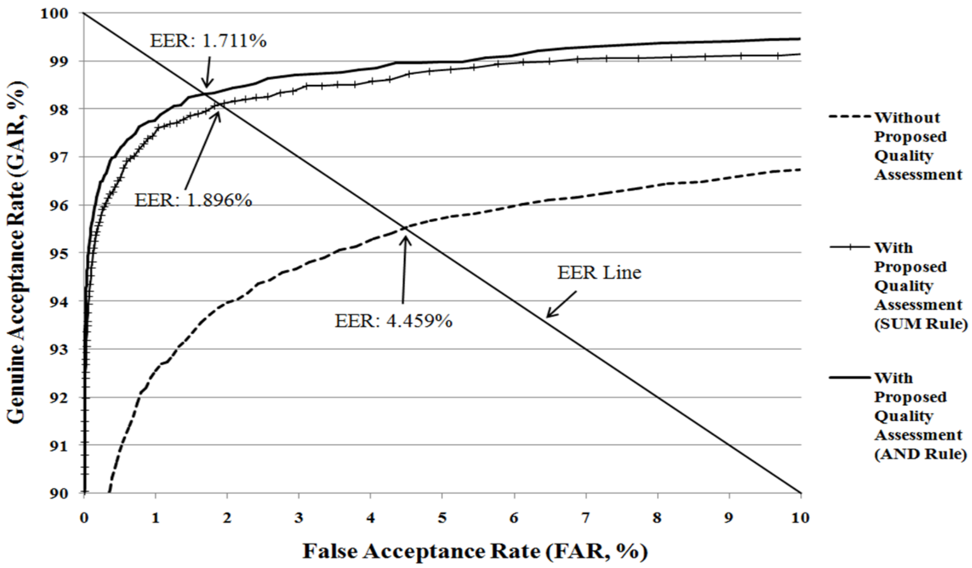
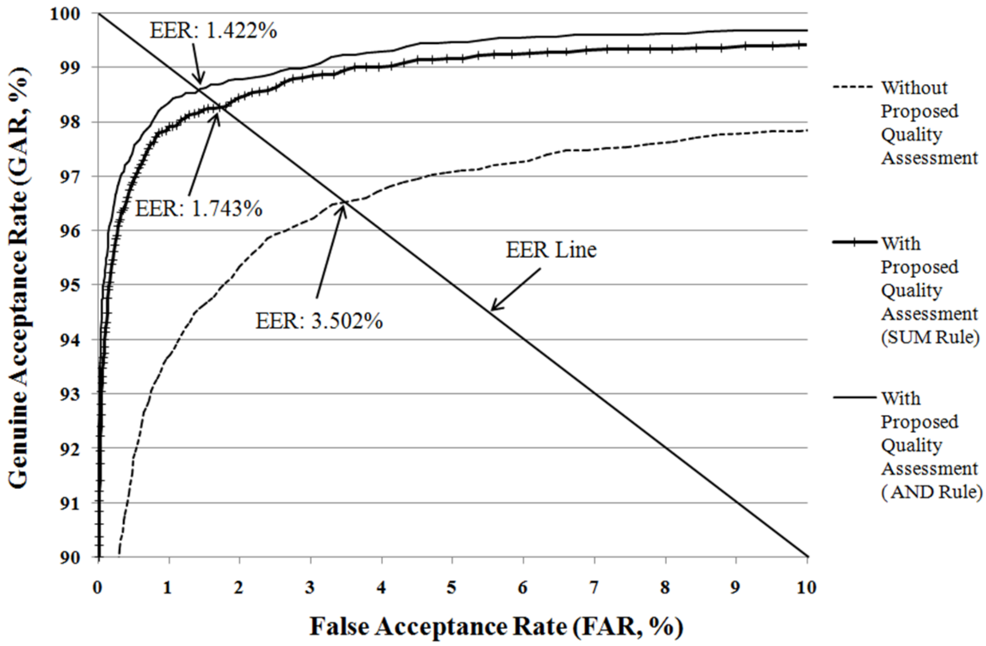


Fig. 14. Average ROC curves with and without the proposed method (using "Database 2")

In the next experiment, we measured the accuracy using a recognition algorithm that was different from the LBP-based finger-vein recognition used in **Fig. 12** and **Fig. 14**. In these experiments, we used a Gabor-filter-based finger-vein recognition algorithm [26]. Two types of Gabor filters (15 and 25 kernels) were tested.



(a)



(b)

Fig. 15. The ROC curves of finger-vein recognition for "Database 1" using Gabor filtering (15 and 25 kernels) with and without the proposed quality assessment method: (a) based on 15 kernels and (b) based on 25 kernels

Fig. 15 shows that the accuracies of the proposed quality assessment with the SUM and AND rules were higher than those without the proposed quality assessment method. These results and those shown in **Fig. 12** confirmed that the proposed quality assessment method performed best, irrespective of the type of finger-vein recognition algorithm. The procedure for matching by bit-shifting was newly adopted in Gabor-filter-based recognition, so the EER without the proposed quality assessment method in **Fig. 15** was lower than that in a previous study [26]. As shown in **Fig. 12**, **Fig. 14**, and **Fig. 15**, the AND rules gave better performance than the SUM rules for the following reason. With the AND rules, both the enrolled and input images were good-quality images because the following conditions were satisfied: "the quality score (FVQ in Eq. 2) of the enrolled image was greater than the threshold and that of the input image was also higher than the threshold at the same time." However, it is possible that one of the enrolled and input images can be a poor-quality image with the SUM rules because the summed quality score of the enrolled and input image may be greater than the threshold.

In general, the error rates should be considered based on two aspects of the FAR and FRR. Considering only the FRR, the quality estimation may be unnecessary if the LBP feature extraction and Hamming distance classifier are much faster. However, when using poor-quality images, the FAR increases as shown in **Fig. 16**. In each case in **Fig. 16**, the threshold of HD is 0.197. Thus, if the HD calculated during finger-vein recognition is less than 0.197, the input image is accepted; otherwise, it is rejected. In each case in **Fig. 16**, the threshold for FVQ is 0.19. If the FVQs of the two images are both greater than 0.19, an attempt is made to recognize them whereas no attempt at matching is made in other cases.

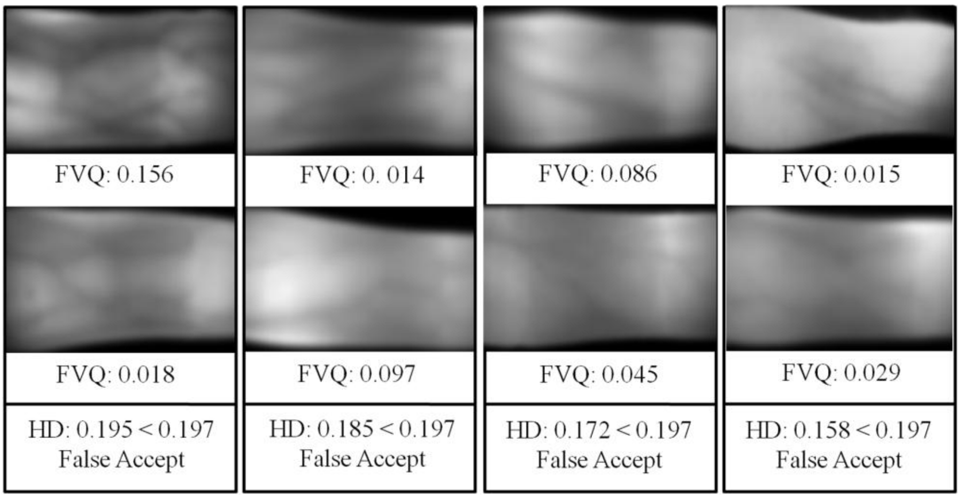


Fig. 16. Examples of false acceptance cases without the proposed quality assessment method

In **Fig. 16**, the two images in the first and second rows are from different fingers (imposter matching), but the HDs are less than the threshold (0.197) in all cases and false acceptances occur. However, with the proposed quality assessment method, no attempt is made at recognition because the FVQs of all the images are less than the FVQ threshold (0.19), and consequently, false acceptances do not occur. Therefore, the proposed quality assessment method is necessary because of this aspect of the FAR.

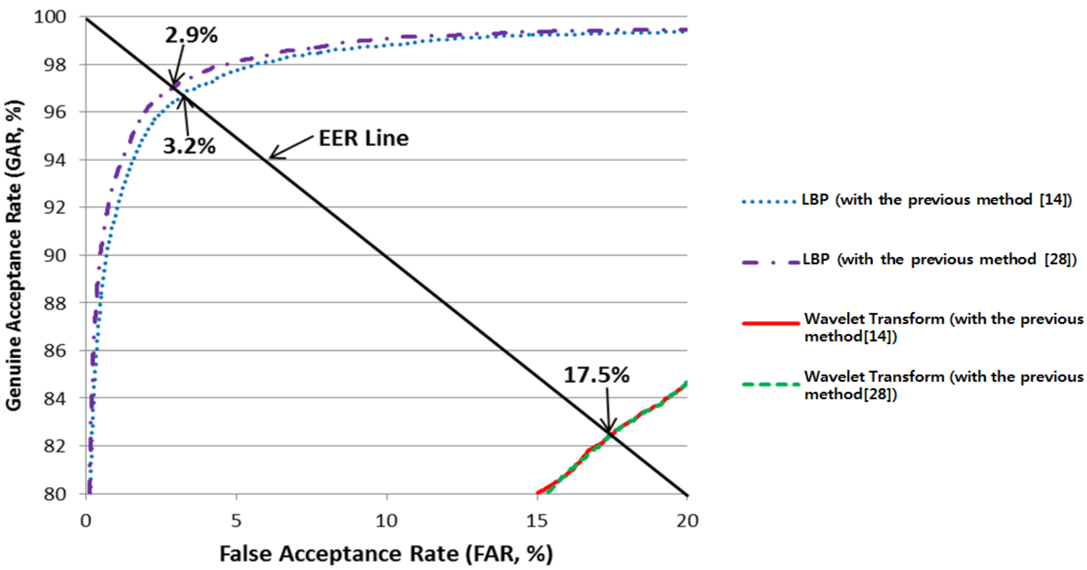


Fig. 17. The ROC curves of finger-vein recognition using previous quality enhancement methods.

In the next test, we compared the accuracy of the proposed finger-vein recognition method with other recognition methods that incorporated with image quality enhancement procedures. A previous study [28] proposed a finger-vein recognition method with image quality enhancement based on adaptive Gabor filters and a gray morphological operation. Another previous study [14] proposed an image quality enhancement method using a multi-channel

Gabor filter where a multi-channel Gabor filter used various directions and frequencies to enhance the finger-vein image's quality without determining the specific direction and width of the vein to which it was applied. To ensure fair comparisons, we used the same database ("Database 1") in this test. As shown in **Fig. 17**, the smallest EER with the previous image quality enhancement method [28] was 2.9% with the LBP-based finger-vein recognition, which was higher than that (2.145%) with the proposed image quality assessment using the same LBP-based recognition method in **Fig. 12 (b)**. In addition, the smallest EER with the previous image quality enhancement method [14] was 3.2% using the LBP-based finger-vein recognition, which was also higher than that (2.145%) with the proposed image quality assessment using the same LBP-based finger-vein recognition in **Fig. 12 (b)**. As shown in **Fig. 12**, **Fig. 14**, **Fig. 15**, and **Fig. 17**, the accuracy of finger-vein recognition (considering the FAR and FRR) using the proposed quality assessment method was higher than that without the quality assessment and those reported with previous methods [14][20][28].

4. Conclusion

This study developed a new finger-vein recognition method that considered the quality of finger-vein images. The quality of the finger-vein image was assessed based on the NDVP, which incorporated the depth of the vein line and the complexity of the vein line structure in the finger-vein image. Using the quality scores of the finger-vein images, the recognition system could eliminate poor-quality images while retaining good-quality images for recognition. The experimental results confirmed that the performance of the proposed quality assessment method was better than that of previous methods.

References

[1] A. K. Jain, A. Ross and S. Prabhakar, "An introduction to biometric recognition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, issue 1, pp. 4-20, January, 2004. Article (CrossRef Link)

[2] 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, issue 3, pp. 179-186, September, 2009. Article (CrossRef Link)

[3] N. Miura, A. Nagasaka and T. Miyatake, "Extraction of finger-vein patterns using maximum curvature points in image profiles," in *Proc. of Conference on Machine Vision Applications (MVA)*, May 16-18, 2005. http://b2.cvl.iis.u-tokyo.ac.jp/mva/proceedings/CommemorativeDVD/2005/papers/2005347.pdf

[4] W. Pi, J. Shin and D. Park, "An effective quality improvement approach for low quality finger-vein image," in *Proc. of Int. Conference on Electronics and Information Engineering (ICEIE)*, vol. 1, pp. 424-427, August 1-3, 2010. Article (CrossRef Link)

[5] Y. Chen, S. C. Dass and A. K. Jain, "Fingerprint quality indices for predicting authentication performance," in *Proc. of the 5th Int. Conference on Audio- and Video- Based Biometric Person Authentication (AVBPA)*, pp. 160-170, July 20-22, 2005. Article (CrossRef Link)

[6] http://www.nist.gov/itl/iad/ig/nbis.cfm (accessed on November 26, 2012)

[7] L. Hong, A. Jian, S. Pankanti and R. Bolle, "Fingerprint enhancement," in *Proc. of the 3rd IEEE Workshop on Applications of Computer Vision (WACV)*, pp. 202-207, December 2-4, 1996. Article (CrossRef Link)

[8] M. Wen, Y. Liang, Q. Pan and H. Zhang, "A gabor filter based fingerprint enhancement algorithm in wavelet domain," in *Proc. of IEEE Int. Symposium on Communications and Information Technology (ISCIT)*, vol. 2, pp. 1468-1471, October 12-14, 2005. Article (CrossRef Link)

[9] S. Greenberg, M. Aladjem, D. Kogan and I. Dimitrov, "Fingerprint image enhancement using

filtering techniques," in *Proc. of 15th Int. Conference on Pattern Recognition*, vol. 3, pp. 322-325, September 3-7, 2000. Article (CrossRef Link)
[10] A. Almansa and T. Linderberg, "Fingerprint enhancement by shape adaptation of scale-space operators with automatic scale selection," *IEEE Transactions on Image Processing*, vol. 9, issue 12, pp. 2027-2042, December, 2000. Article (CrossRef Link)
[11] S. Chikkerur, A. N. Cartwright and V. Govindaraju, "Fingerprint enhancement using STFT analysis," *Pattern Recognition*, vol. 40, issue 1, pp. 198-211, January, 2007. Article (CrossRef Link)
[12] H. Sellahewa and S. A. Jassim, "Image-quality-based adaptive face recognition," *IEEE Transactions on Instrumentation and Measurement*, vol. 59, issue 4, pp. 805-813, April, 2010. Article (CrossRef Link)
[13] A. S. Georghiades, D. J. Kriegman and P. N. Belhurneur, "Illumination cones for recognition under variable lighting: face," in *Proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 52-58, June 23-25, 1998. Article (CrossRef Link)
[14] J. Yang and J. Yang, "Multi-channel gabor filter design for finger-vein image enhancement," in *Proc. of 5th Int. Conference on Image and Graphics (ICIG)*, pp. 87-91, September 20-23, 2009. Article (CrossRef Link)
[15] J. Zhang and J. Yang, "Finger-vein image enhancement based on combination of gray-level grouping and circular gabor filter," in *Proc. of Int. Conference on Information Engineering and Computer Science (ICIECS)*, pp. 1-4, December 19-20, 2009. Article (CrossRef Link)
[16] J. Yang and M. Yan, "An improved method for finger-vein image enhancement," in *Proc. of IEEE 10th Int. Conference on Signal Processing (ICSP)*, pp. 1706 - 1709, October 24-28, 2010. Article (CrossRef Link)
[17] J. Yang and B. Zhang, "Scattering removal for finger-vein image enhancement," in *Proc. of Int. Conference on Hand-Based Biometrics(ICHB)*, pp. 1-5, November 17-18, 2011. Article (CrossRef Link)
[18] J. Yang and W. Wang, "Finger-vein image enhancement based on orientation field," in *Proc. of Int. Conference on Hand-Based Biometrics(ICHB)*, pp. 1-6, November 17-18, 2011. Article (CrossRef Link)
[19] M. Sheng, Y. Zhao, D. Zhang and S. Zhuang, "Quantitative assessment of hand vein image quality with double spatial indicators," in *Proc. of Int. Conference on Multimedia Technology (ICMT)*, pp. 642-645, July 26-28, 2011. Article (CrossRef Link)
[20] Y. Zhao and M. Sheng, "Application and analysis on quantitative evaluation of hand vein image quality," in *Proc. of Int. Conference on Multimedia Technology (ICMT)*, pp. 5749-5751, July 26-28, 2011. Article (CrossRef Link)
[21] K. Lin, F. Han, Y. Yang and Z. Zhang, "Feature level fusion of fingerprint and finger-vein biometrics," in *Proc. of the 2nd Int. Conference on Advances in Swarm Intelligence (ICSI)*, vol. Part II, June 12-15, 2011. Article (CrossRef Link)
[22] D. Hartung, S. Martin and C. Busch, "Quality estimation for vascular pattern recognition," in *Proc. of Int. Conference on Hand-Based Biometrics (ICHB)*, pp.1-6, November 17-18, 2011. Article (CrossRef Link)
[23] S. Z. Li and A. K. Jain, *Encyclopedia of Biometrics*, Springer, 2009. http://www.springer.com/computer/image+processing/book/978-0-387-73002-8
[24] http://webstore.iec.ch/preview/info_isoiec29794-1%7Bed1.0%7Den.pdf (accessed on November 26, 2012)
[25] http://biometrics.org/bc2009/presentations/tuesday/Tabassi%20MR%2014%20Tue%20935-1000.pdf (accessed on November 26, 2012)
[26] D. T. Nguyen, Y. H. Park, H. C. Lee, K. Y. Shin, B. J. Kang and K. R. Park, "Combining touched fingerprint and finger-vein of a finger, and its usability evaluation," *Advanced Science Letters*, vol. 5, no. 1, pp. 85-95, January, 2012. Article (CrossRef Link)
[27] Z. Zhu and T. S. Huang (eds.), *Multimodal Surveillance: Sensors, Algorithms and Systems*, Artech House, MA, 2007.
http://www.amazon.com/Multimodal-Surveillance-Sensors-Algorithms-Systems/dp/1596931841

[28] Y. H. Park and K. R. Park, "Image quality enhancement using the direction and thickness of vein lines for finger-vein recognition," *International Journal of Advanced Robotic Systems*, vol. 9(154), pp. 1-10, October, 2012. Article (CrossRef Link)

Dat Tien Nguyen received a B.S. degree in electronics and telecommunication technology from Hanoi University of Technology, Hanoi, Vietnam, in 2009. He is currently pursuing a combined Masters' and Ph.D. degree in electronics and electrical engineering at Dongguk University. His research interests include biometrics and image processing.

Young Ho Park received a B.S. and a Masters' degree in electronics engineering from Dongguk University, Seoul, Korea, in 2010 and 2012, respectively. He is currently pursuing a Ph.D. in electronics and electrical engineering at Dongguk University. His research interests include image processing and pattern recognition.

Kwang Yong Shin received a B.S. degree in electronics engineering from Dongguk University, Seoul, South Korea, in 2009. He is currently pursuing a combined Masters' and Ph.D. degree in electronics and electrical engineering at Dongguk University. His research interests include biometrics and image processing.

Kang Ryoung Park received his B.S. and Masters' degrees in electronic engineering from Yonsei University, Seoul, Korea, in 1994 and 1996, respectively. He also received his Ph.D. in computer vision from the Department of Electrical and Computer Engineering at Yonsei University in 2000. He was an assistant professor in the Division of Digital Media Technology at Sangmyung University from March 2003 to February 2008. He has been an assistant and associate professor in the division of Electronics and Electrical Engineering at Dongguk University since March 2008. His research interests include computer vision, image processing, and biometrics.