

A Direction-Based Vascular Pattern Extraction Algorithm for Hand Vascular Pattern Verification

Sang Kyun Im, Hwan Soo Choi, and Soo-Won Kim

This paper proposes an improved vascular pattern extraction algorithm for person verification applications. The proposed direction-based vascular pattern extraction (DBVPE) algorithm is based on the directional information of vascular patterns. It applies two different filters to the input images: row vascular pattern extraction filter (RVPEF) for effective extraction of the abscissa vascular patterns and column vascular pattern extraction filter (CVPEF) for effective extraction of the ordinate vascular patterns. We use the combined output of both filters to obtain the final hand vascular patterns. Unlike the conventional hand vascular pattern extraction algorithm, the directional extraction approach prevents loss of the vascular pattern connectivity. To validate the DBVPE algorithm, we used a prototype system with a DSP processor. The prototype system shows approximately a three-times better false acceptance rate (FAR) than the conventional single filter algorithm.

I. INTRODUCTION

Biometrics is a technology that verifies or identifies persons using their physiological or behavioral characteristics. As our society is moving at light speed into the information age, the demand for biometric technology is growing at a much faster rate.

There are several modalities for biometric person verification: fingerprint systems, retina/iris systems [1], [2], hand geometry systems, hand vascular systems, etc. Each of these systems has merits and demerits. For example, fingerprint technology has an advantage in its implementation size and uniqueness of biometric features [3], [4], but it has severe problems in usability [5]. Usability is defined as the percentage of an unspecified population that is capable of using a technology. Because of the lack of usability, it is difficult to apply fingerprint technology to work places such as factories, construction sites, and places with inferior environments. Hand geometry technology [6] shows excellent performance in the usability measure, but it suffers from a relatively high false acceptance rate (FAR) measure. In spite of its disadvantage, it occupies the second largest market share in the US biometrics market, mainly because of its good usability.

Hand vascular technology is excellent in the usability measure and has many advantages because it uses biometric features inside the human body rather than on the surface, and this results in a very stable verification performance during long periods of time.

The problem with conventional hand vascular technology [7], [8], however, is that the vascular pattern is extracted without considering the directional characteristics of the vascular patterns. As a result, there is some loss of connectivity of vascular patterns and verification

Manuscript received June 4, 2002; revised Oct. 24, 2002.

This work was supported in part by Biometrics Engineering Research Center.

Sang Kyun Im (phone: +82 2 523 4715, e-mail: isk@tech-sphere.com) is with TechSphere Co. Ltd., Seoul, Korea.

Hwan Soo Choi (e-mail: hschoi@mju.ac.kr) is with the Department of Information Engineering, Myong-ji University, Seoul, Korea.

Soo-Won Kim (e-mail: ksw@asic.korea.ac.kr) is with the Department of Electronics Engineering, Korea University, Seoul, Korea.

performance degradation in terms of its FAR. The impact of this problem is more severe with subjects who have relatively thin vascular patterns or a contracted vascular pattern due to various conditions, such as exposure to cold. This paper specifically focuses on minimizing loss of the vascular pattern connectivity.

In order to reduce the impact of the loss of vascular pattern connectivity, we propose a new algorithm, called the direction-based vascular pattern extraction (DBVPE) algorithm. It applies two different preprocessing filters to the input images: row vascular pattern extraction filter (RVPEF) for effective extraction of the abscissa vascular patterns and column vascular pattern extraction filter (CVPEF) for effective extraction of the ordinate vascular patterns. We combine the output of both the filters to obtain the final hand vascular patterns. Our investigation demonstrated that the directional extraction approach substantially reduced loss of vascular pattern connectivity compared to the conventional hand vascular pattern extraction algorithm. The main purpose of the RVPEF is to effectively extract the abscissa vascular patterns while preserving pattern connectivity and that of the CVPEF is to effectively extract the ordinate vascular patterns while preserving pattern connectivity.

The proposed DBVPE algorithm preserves connectivity information by minimizing loss of both the abscissa and ordinate vascular pattern information. Using DBVPE in constructing our algorithm for hand vascular pattern person verification, we observed substantial success in resolving critical problems of the conventional hand vascular pattern extraction algorithm.

To test and validate the DBVPE algorithm, we devised a prototype system, the hand vascular pattern recognition system (HVPRS), to implement the DBVPE algorithm. To effectively implement the hardware, we designed the filters to have filter coefficients to the power of two, which enabled implementation with fixed-point operators only. In this paper, we describe the DBVPE algorithm and the HVPRS in detail and present the results of the performance evaluation of DBVPE.

To demonstrate the performance improvement of our algorithm over the conventional single filter algorithm, which does not utilize directional information, we first analyzed the conventional algorithm as well as the DBVPE algorithm; this is described in section II. In section III, we then present the implementation details of the DBVPE algorithm and the HVPRS. Section IV contains the results of the performance evaluation and the experimental results. Finally, in section V, we conclude this paper with a presentation of the future direction of the research.

II. CONVENTIONAL HAND VASCULAR PATTERN EXTRACTION ALGORITHM

We first summarize some problems of the conventional vascular pattern extraction algorithm proposed by Hong et al. and Im et al. [8]-[10] and then compare it with the proposed DBVPE.

We found that the hand vascular pattern image processed by the conventional algorithm shows some loss of information in vascular pattern connectivity, mainly because the algorithm does not allow for the fact that the vascular pattern of a person includes directional information and the vascular thickness of a person may vary for some reasons, such as a blood pressure change or a variation in temperature. Thus, the algorithm will show performance degradation if the subject is exposed to cold weather or suffers an abnormal blood pressure change. The main reason of the performance degradation of the conventional single filter approach is that it does not consider directional information of the hand vascular patterns.

For implementing the algorithm, we designed each of the filter coefficients [9], [10] with a 7-tap canonical signed digit (CSD) [11], [12] code for fixed-point operation.

The filter coefficient design of the proposed DBVPE algorithm, however, is based on numbers in the form of the power of two, which reduces the calculation complexity and greatly improves algorithm performance. Figure 1 shows the flow diagram of the filtering process for the conventional algorithm starting from the original raw image taken by a standard charge coupled device (CCD) camera. As shown in the flow diagram, the algorithms do not allow for the located vascular pattern direction.

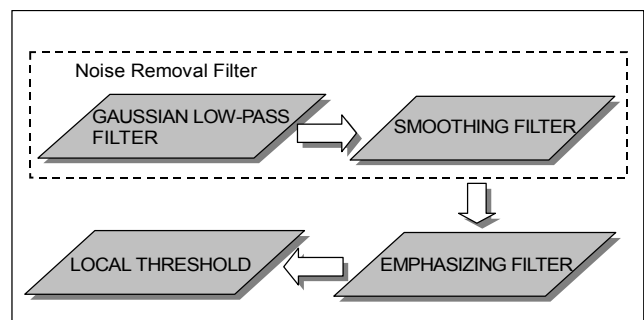


Fig. 1. Processing flow diagram of the conventional algorithm.

1. Noise Removal Filter

The noise removal filter of the conventional algorithm consists of a Gaussian low-pass filter and a smoothing filter. The Gaussian low-pass filter removes speckle noise in the image. The smoothing filter removes thermal and burst noise. The Gaussian low-pass filter and smoothing filter consists of an

11×11 kernel-mask and each of the filter coefficients is made up by a 7-tap CSD code, so that the implemented hardware requires fixed-point operations with seven barrel-shifters and six adders.

The filtering process of the noise removal filter of the conventional algorithm is implemented in the spatial domain, that is, it is implemented by convolution masking. The gray levels assigned to each and every pixel of the filtered images are the weighted sum obtained when the center of the filter mask is located on the corresponding pixel of the input images. Noise removal filters of the conventional algorithm [9], [10] can be expressed as in (1) and (2).

$$z(x_c, y_c) = \sum_{x=1}^M \sum_{y=1}^M z(x, y) w(x, y) \quad (1)$$

with $w(x, y)$ being equal to

$$w(x, y) = \sum_{tap=1}^7 S_{tap}(x, y) 2^{-K_{tap}(x, y)}, \quad (2)$$

where $z(x_c, y_c)$, M , and $w(x, y)$ are the center pixel of the filter mask, the vector size of the kernel mask, and the conventional preprocessing filter coefficient, respectively; $S_{tap}(x, y)$ is one of $\{-1, 0, 1\}$, and $K_{tap}(x, y)$ is any integer number.

2. Emphasizing Filter for Hand Vascular Patterns

After the noise removal filter is applied, the emphasizing filter for hand vascular patterns is applied to emphasize the hand vascular pattern in the noise-removed images. The conventional emphasizing filter, in fact, takes the form of a band-pass filter as shown in Fig. 2.

As the figure shows, the pass band gain of the conventional filter is not uniform and the gain drop is not sharp enough around the low frequency stop band. We found that these filter characteristics cause information loss when the vascular pattern

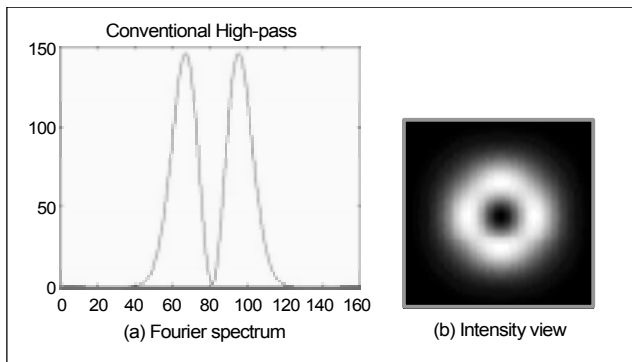


Fig. 2. The characteristics of the conventional emphasizing filter (circular symmetric).

is extracted mainly because the conventional filter is not optimized for directional information. Some of the edge information of thin vascular patterns, which resides in the high frequency band, is also lost. As a result, the pattern vectors that contain the connectivity information of the abscissa vascular patterns and the ordinate vascular patterns are partially lost, causing degradation of the performance of the conventional hand vascular pattern recognition system.

III. PROPOSED HAND VASCULAR PATTERN EXTRACTION ALGORITHM

As already mentioned, the extracted vascular patterns using the conventional algorithm showed substantial loss of pattern connectivity. In order to resolve this problem, the proposed DBVPE algorithm uses the RVPEF and CVPEF and combines the output of both filters to construct the final hand vascular pattern. The RVPEF and CVPEF effectively extract the abscissa components and ordinate components of vascular patterns, respectively. Figure 3 presents a processing flow diagram of the proposed DBVPE algorithm.

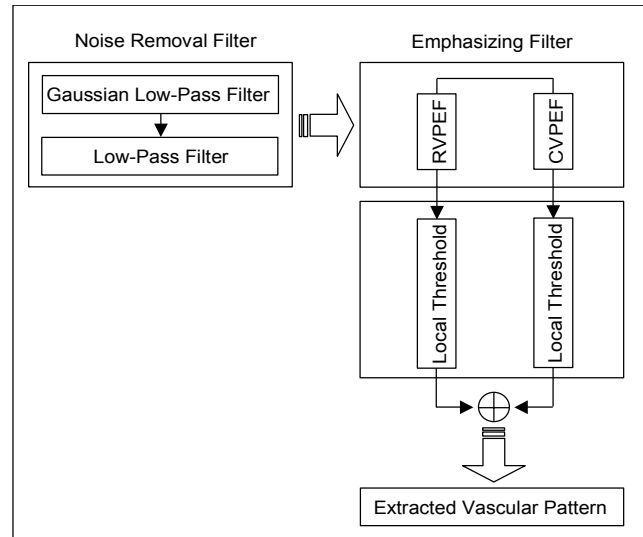


Fig. 3. Processing flow diagram of the proposed DBVPE algorithm.

1. Noise Removal Filter

The noise removal filter of the proposed algorithm consists of a Gaussian low-pass filter and a smoothing filter, which are identical to those of the conventional filter. In order to reduce the calculation complexity further, however, we designed the filter coefficients of the noise removal filters of the DBVPE algorithm with numbers in the form of the power of two. With this design, the noise removal filter can be processed by

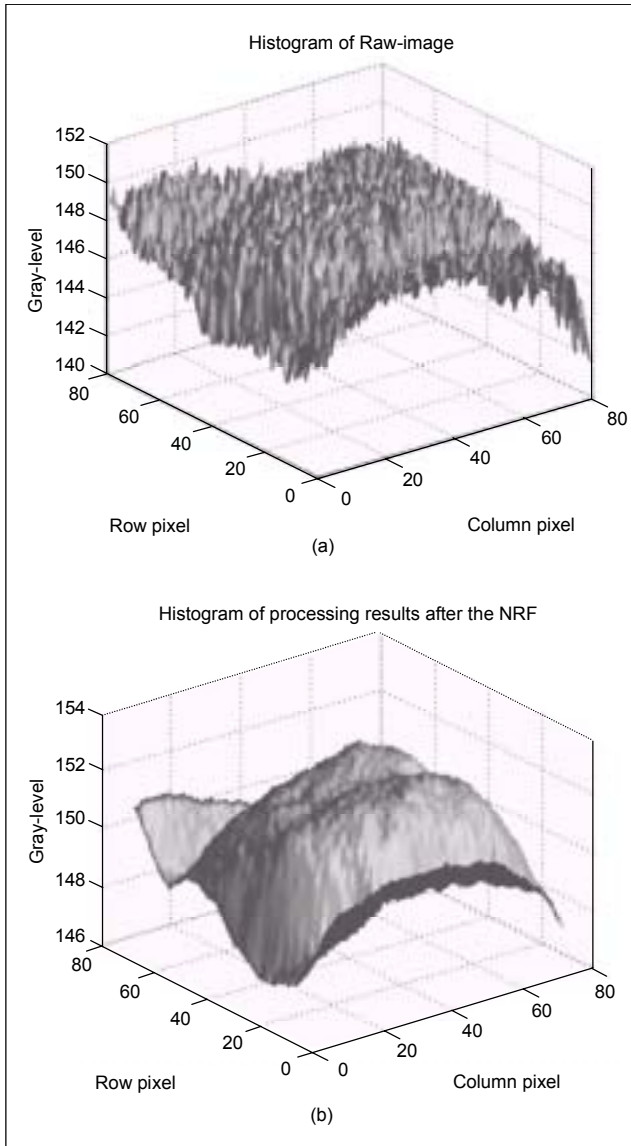


Fig. 4. (a) Histogram of the partially separated ROI image, (b) histogram of processing results for the noise removal filter.

fixed-point operation. The original image can include thermal and burst noise (Fig. 4(a)). Figure 4(b) shows the noise-removed image in the processing results of the noise removal filter.

As the conventional noise removal filter is expressed in (1) and (2), the proposed filter is expressed in (3) and (4).

$$z(x_c, y_c) = \sum_{x=1}^M \sum_{y=1}^M z(x, y) w(x, y) \quad (3)$$

with $w(x, y)$ being equal to

$$w(x, y) = 2^{-K(x, y)}, \quad (4)$$

where $z(x_c, y_c)$, M , $w(x, y)$, and $K(x, y)$ are the center pixels of the filter mask, the vector size of the kernel mask, the noise removal filter coefficient of the DBVPE algorithm, and any integer, respectively. As given in (3), the noise removal filter coefficients of the DBVPE algorithm are expressed as numbers in the form of the power of two, which makes it possible to perform the filtering process using only fixed-point operations.

2. Emphasizing Filter for Hand Vascular Patterns

After the noise removal filter is applied, the emphasizing filter for hand vascular patterns is applied to emphasize the hand vascular pattern in the noise-removed images. The proposed emphasizing filter of the DBVPE algorithm consists of two different filters, the RVPEF and the CVPEF. Basically, the RVPEF and CVPEF are designed to obtain better performance in preserving connectivity information along horizontal-direction vascular patterns and vertical-direction vascular patterns, respectively, than the conventional hand vascular pattern extraction algorithm.

The RVPEF has an 11×17 kernel with horizontally oriented characteristics (Fig. 5), and the CVPEF has the same size kernel

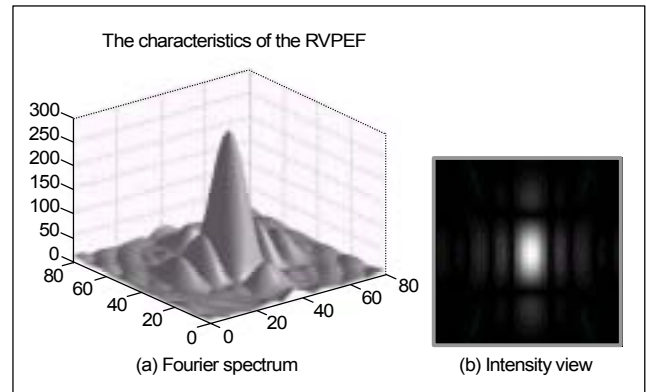


Fig. 5. The characteristics of the RVPEF.

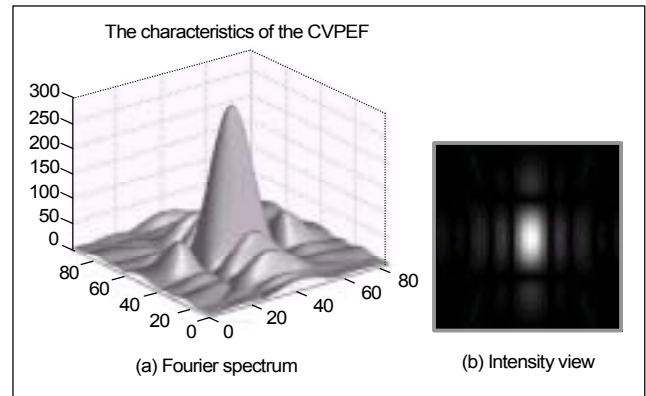


Fig. 6. The characteristics of the CVPEF.

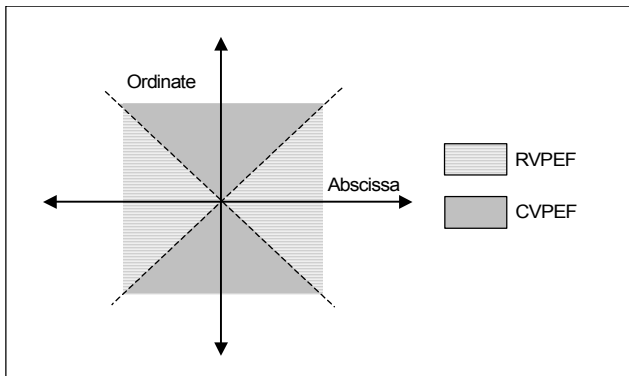


Fig. 7. The coverage areas of the RVPEF and the CVPEF.

but with vertically oriented characteristics (Fig. 6). Compared to the conventional hand vascular pattern extraction algorithm, these filters more effectively extract vascular patterns by preserving pattern connectivity information. The coverage areas of the RVPEF and CVPEF are shown in Fig. 7.

In order to construct the final vascular pattern, we apply an OR operation to the output of the RVPEF and CVPEF. We observed that combining the RVPEF and CVPEF resulted in extracted vascular patterns that follow the true patterns more closely.

The filters of the proposed RVPEF and CVPEF can be expressed as in (5) and (6).

$$z(x_c, y_c) = \sum_{x=1}^M \sum_{y=1}^N z(x, y) w(x, y) \quad (5)$$

with $w(x, y)$ being equal to

$$w(x, y) = S_{(x, y)} 2^{-K_{(x, y)}}, \quad (6)$$

where $z(c)$, M , N , and $w(i)$ are the center pixels of the filter mask, the abscissa vector size of the mask, the ordinate vector size of the mask, and the filter coefficient of the proposed emphasizing filter, respectively. $S_{(x, y)}$ is one of $\{-1, 1\}$ and

$K_{(x, y)}$ is any integer number. As shown in the equations, the coefficients of the RVPEF and CVPEF are designed with numbers in the form of the power of two, which makes it possible to perform the filtering process using only fixed-point operations. Table 1 presents an example of the proposed emphasizing filter coefficients. Since we designed the coefficients in a separable way [13], the filter coefficients are presented in the form of a 1-D array.

Figure 8 presents a block diagram of the prototype hand vascular recognition system built around the proposed DBVPE algorithm. In the block diagram, the video decoder unit decodes the video signal from a CCD camera. The size of the image input to the digital signal processor (DSP) is 320×240 pixels. The DSP processor is the main block where the proposed DBVPE algorithm is implemented with a Gaussian low-pass filter, a smoothing filter, an emphasizing filter, and the threshold process. After applying the DBVPE filter, a median filter [10] removes the noise caused by hair, skin curvatures, and fatty substances under the skin.

A normalization and data base process is used to store each user's template vascular data in the memory and is required for the user enrollment process. The final hand vascular pattern is available after this process.

Figure 9 is a photographic picture of the prototype HVPRS system. The system comprises a user interface block for registering users and indicating the verification result, a microprocessor to match the input pattern and template pattern, a DSP processor for extracting the hand vascular pattern from the input image, and a flash memory for template data storage.

IV. PERFORMANCE EVALUATION

Before presenting the quantitative evaluation results, we describe a brief qualitative experimental result. We processed test images using both the conventional and proposed algorithm. Figure 10(a) shows the raw image of the partially separated region of interest (ROI) image, and Figs. 10(b) and

Table 1. Filter coefficients for the proposed emphasizing filter.

Emphasizing filter coefficient (11×1 kernel mask)	1	2	3	4	5	6	7	8	9	10	11
	-2^0	-2^0	2^1	2^2	2^4	2^5	2^4	2^2	2^1	-2^0	-2^0
Emphasizing filter coefficient (17×1 kernel mask)	1	2	3	4	5	6	7	8	9	10	11
	-2^0	-2^0	-2^0	-2^0	-2^0	2^1	2^3	2^4	2^5	2^4	2^3
	12	13	14	15	16	17					
	2^1	-2^0	-2^0	-2^0	-2^0	-2^0					

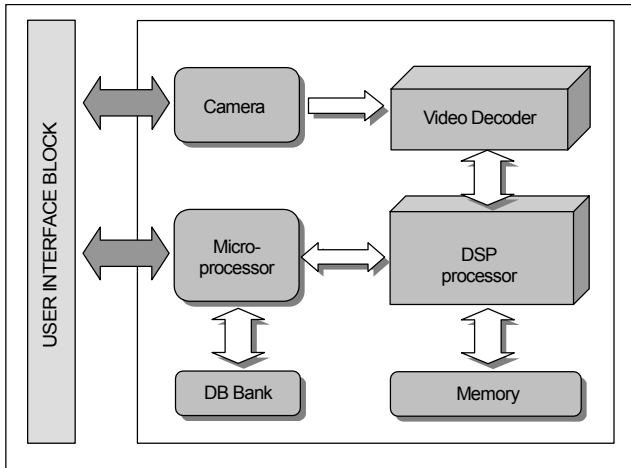


Fig. 8. The block diagram of the prototype HVPRS.

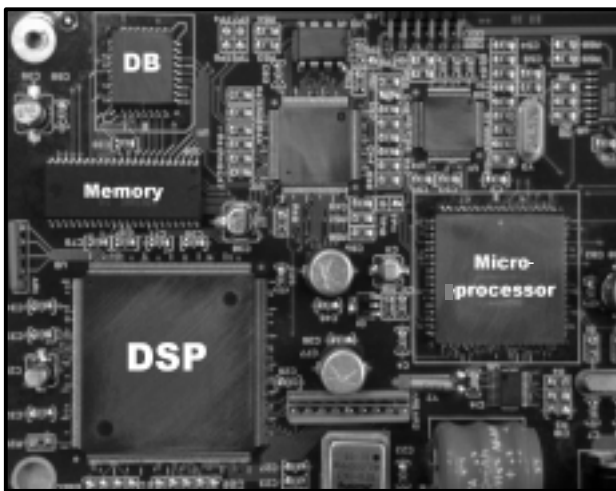


Fig. 9. The realized prototype system.

(c) show the hand vascular pattern extracted by the conventional system. Figure 10(d) shows the pattern extracted by the proposed RVPEF, and Fig. 10(e) shows the pattern extracted by the proposed CVPEF. Figure 10(f) shows the final pattern extracted by the proposed DBVPE algorithm.

In Fig. 10(b), “R” indicates the location where the connectivity of a horizontal vascular component is lost by the conventional algorithm, and in Fig. 10(c), “C” shows an example of connectivity loss in the vertical direction. Figure 10(d) demonstrates that the proposed RVPEF preserves the horizontal connectivity information by minimizing loss of the vascular pattern in the horizontal direction, and the CVPEF preserves the vertical direction connectivity (Fig. 10(e)). Finally, Fig. 10(f) shows an example of the DBVPE output, in which the connectivity information is well preserved.

For a quantitative evaluation of the DBVPE algorithm along with the realized prototype system, we collected a set of hand

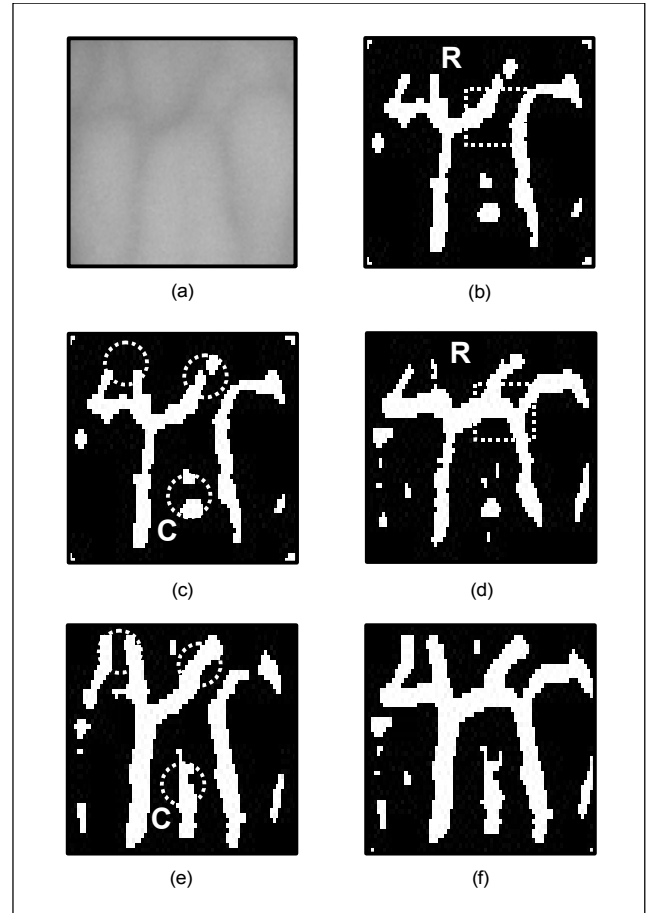


Fig. 10. (a) The raw image of the partially separated ROI image, (b) partial loss of horizontal vascular pattern connectivity of the conventional algorithm, (c) partial loss of vertical vascular pattern connectivity of the conventional algorithm, (d) processing result of RVPEF, (e) processing result of CVPEF, (f) final result of the DBVPE algorithm.

images of 10,000 randomly selected people and processed the test set using both the DBVPE and the conventional algorithm. Usually, the accuracy of biometric systems is represented by the false acceptance rate (FAR). Thus, we obtained the FAR based on the FAR computation method proposed by Jain et al. [14]. Figure 11 is a plot that compares the FAR of both algorithms. In the figure, the error scale is logarithmic. The abscissa of the plot is the threshold level, which is the parameter that determines the verification success (match) or failure. By analyzing the plot, we concluded that the accuracy performance of the proposed algorithm was substantially improved over that of the conventional algorithm.

Generally, the FAR and false rejection rate (FRR) [15] have an inverse relation, that is, as the decision threshold increases, the FAR decreases, and at the same time, the FRR increases. Utilizing the DBVPE algorithm, when we adjusted the threshold level so that an experienced user would feel that the FRR level was acceptable, we observed the system FAR was

about 0.0001%. With the same parameter set, we observed the FAR of the conventional algorithm was worse than 0.01%.

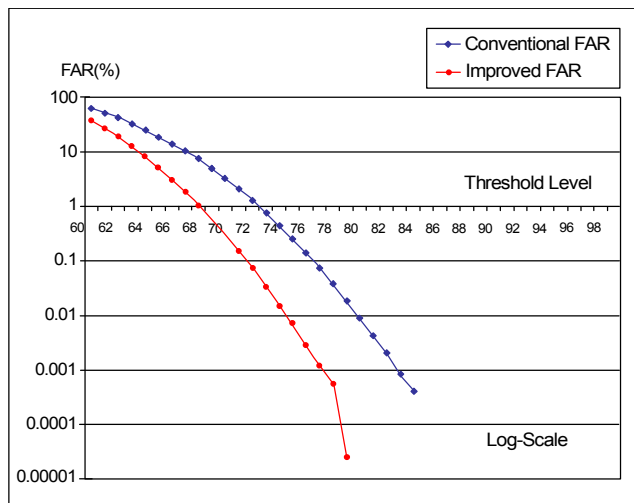


Fig. 11. A plot to compare FAR performance of the vascular pattern recognition system utilizing the conventional algorithm and the proposed DBVPE.

V. CONCLUSION

In this paper, we proposed an algorithm called DBVPE, which effectively extracts the vascular pattern from input hand images. In addition, we implemented a prototype hand vascular pattern verification system with the proposed algorithm. We quantitatively evaluated the effectiveness of the proposed algorithm using this prototype system with both the conventional and DBVPE algorithms.

According to the evaluation results, we concluded that the DBVPE algorithm outperforms the conventional vascular pattern extraction algorithm as judged by FAR metrics. We believe that the improvement was achieved by using the directional information of the vascular pattern to enhance the input images.

In addition, we optimized the filtering algorithm for the DBVPE algorithm for efficient calculation. For example, each of the filter coefficients was designed in the form of the power of two, so that a low-cost fixed-point processor could be utilized.

The next step in our research will be the implementation of a complete person verification system using hand vascular patterns. In order to accomplish this goal, we will continue to work on the development of a more effective image acquisition sensor that can provide users with comfort and convenience. The person verification algorithm should also be enhanced to prevent performance degradation caused by external environments, such as inferior illumination and contamination.

REFERENCES

- [1] Shinyoung Lim, Kwanyong Lee, Okhwan Byeon, and Taiyun Kim, "Efficient Iris Recognition through Improvement of Feature Vector and Classifier," *ETRI J.*, vol. 23, no. 2, June 2001, pp. 61-70.
- [2] Sang-mi Lee, Hee-Jung Bae, and Sung-Hwan Jung, "Efficient Content-Based Image Retrieval Methods Using Color and Texture," *ETRI J.*, vol. 20, no. 3, Sept. 1998, pp. 272-283.
- [3] A.P. Fitz and R.J. Green, "Fingerprint Classification Using a Hexagonal Fast Fourier Transform," *The Journal of the Pattern Recognition Society*, vol. 29, no. 10, 1996, pp. 1587-1597.
- [4] Michale M.S. Chong, T.H. Ngee, L. Jun, and Robert K.L. Gay, "Geometric Framework for Fingerprint Image Classification," *The Journal of the Pattern Recognition Society*, no. 7-9, 1997, pp. 1475-1488.
- [5] CESG X92A/4009309 *Biometric Product Testing Final Report*, UK Government Biometric Working Group, 2001.
- [6] Sanchez Reillo R, Sanchez Avila C, Gonzalez Marcos A, "Biometric Identification through Hand Geometry Measurements," *IEEE Trans. on Pattern Analysis & Machine Intelligence*, vol. 22, no. 10, 2000, pp. 1168-1171.
- [7] G.T. Park, S.K. Im, and H.S. Choi, "A Person Identification Algorithm Utilizing Hand Vein Pattern," *Proc. of Korea Signal Processing Conf.*, vol. 10, no. 1, 1997, pp. 1107-1110.
- [8] D.U. Hong, S.K. Im, and H.S. Choi, "Implementation of Real Time System for Personal Identification Algorithm Utilizing Hand Vein Pattern," *Proc. of IEKK Fall Conf.*, 1999, vol. 22, no. 2, pp. 560-563.
- [9] S.K. Im, H.M. Park, S.W. Kim, C.K. Chung, and H.S. Choi, "Improved Vein Pattern Extracting Algorithm and its Implementation," *Proc. of IEEE ICCE*, 2000, pp. 2-3.
- [10] S.K. Im, H.M. Park, and S.W. Kim, "A Biometric Identification System by Extracting Hand Vein Patterns," *Journal of the Korean Physical Society*, vol. 38, no. 3, 2001, pp. 268-272.
- [11] Mitsuhiro Yagyu, Akinori Nishihara, and Nobuo Fujii, "Design of FIR Digital Filters Using Estimates of Error Function over CSD Coefficient Space," *IEICE Trans. Fundamentals*, vol. E79, no. 3, 1996, pp. 283-290.
- [12] Reid M. Hewlitt, Earl S. Swartzlander, "Canonical Signed Digit Representation for FIR Digital Filters," *Proc. of the 2000 IEEE Workshop on Signal Processing Systems*, 2000, pp. 416-426.
- [13] Francisco J. Sanchez-Marin, "Automatic Segmentation of Contours of Corneal Cells," *Computer in Biology and Medicine* 29, 1999, pp. 243-258.
- [14] A.K. Jain, L. Hong, and R. Bolle, "On-Line Fingerprint Verification," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 19, no. 4, 1997, pp. 302-314.
- [15] Matteo Golfarelli, Dario Maio, Davide Maltoni, "On the Error-Reject Trade-Off in Biometric Verification Systems," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, 1997, pp. 786-796.



Sang Kyun Im received his BS and MS degrees in electrical engineering from Myongji University, Korea, in 1993 and 1995. He received his PhD degree in electronics engineering from Korea University, Korea, in 2001. He is now a Chief Technical Officer of TechSphere Co., Ltd. His research interest is in the fields of biometrics, SOC, and image processing.



Hwan Soo Choi was born in Busan, Korea in 1961. He received his BS degree in control and instrumentation engineering from Seoul National University, Korea in 1984 and the MS and PhD degrees in electrical engineering from University of Washington at Seattle, in 1986 and 1990. He was a Senior Research Engineer at Laboratory of Computers of LG Electronics Co., Ltd. from 1990 to 1992. He is now a Professor at Myongji University. His research interest is in the field of biometrics, image processing and computer vision.



Soo-Won Kim received his BS degree in electronics engineering from Korea University, Korea in 1974 and MS and PhD degrees in electrical engineering from Texas A&M University in 1983 and 1987. He joined the Department of Electronics Engineering at Korea University as an Assistant Professor in 1987. Since 1989, he has been a Professor in Department of Electronics Engineering at Korea University, Korea.