Computer Technology and Application 7 (2016) 65-72
doi: 10.17265/1934-7332/2016.02.001

Intra-Palm Propagation Signals as Suitable Biometrics for Successive Authentication

Takashi Inada, Yuuta Sodani and Isao Nakanishi

Graduate School of Engineering, Tottori University, Tottori 680-8552, Japan

Abstract: We propose the use of intra-palm propagation signals as biometrics. The intra-palm propagation signal is a signal that is propagated in the shallow part of the skin of a palm. In this paper, we prepare dedicated measuring devices and measure intra-palm propagation signals from twenty-one experimental subjects. We also evaluate the verification performance based on Euclidian distance or SVM (support vector machine). The equal error rate in the case of SVM is approximately 24%.

Key words: Biometrics, successive authentication, intra-palm propagation signal, support vector machine.

1. Introduction

In the case of the user management of systems, successive authentication, such as continuous authentication [1] or on-demand authentication [2], wherein users are required to successively present their biometric data, is required because one-time-only authentication is not capable of preventing identity fraud. Therefore, the password and the ID (identification) card are inapplicable, and only biometric authentication is applicable. Biometric traits that enable the unconscious (transparent) presentation of biometric data are suitable.

The face and the ear are nominated as candidates for this transparent biometrics; however, their data can be insidiously captured by others. This fact enables hackers to produce fakes, which can be used to impersonate genuine users. We confirmed that a face authentication system accepted our faces, which were printed on paper.

Thus, we have proposed the use of intra-body propagation signals as biometrics [3-5]. An intra-body propagation signal is a signal that is propagated on the skin surface. Because the body composition of people differs, the characteristics of the propagated signal also differ. Because intra-body propagation signals are not exposed on the body surface, they are not easily extracted without being noticed. Thus, the intra-body propagation signal may be useful as a new biometric trait.

In conventional studies [3-5], signals propagated on forearms were measured and their verification performance was evaluated. However, the usability of measuring signals on forearms is not satisfactory.

Considering applications for user management, users control a system while gripping or touching part of the system, such as a handle of a vehicle or a mouse device of a computer. In this situation, palms serve as an interface between the system and the user.

In this paper, we propose the use of intra-palm propagation signals as a new biometric modality, which is suitable for successive authentication. In Sect. 2, we explain about the measurement of intra-palm propagation signals. Next, we introduce the feature extraction and verification method in Sect. 3. In Sect. 4, the verification performance of intra-palm propagation signals is evaluated in the experiments using twenty-one experimental subjects. Finally, the concluding remarks are presented in Sect. 5.

Corresponding author: Isao Nakanishi, Doctor of engineering, professor, research fields: signal processing and biometrics.

2. Measurement of Intra-Palm Propagation Signals

Fig. 1 shows a principled structure for measuring intra-palm propagation signals. It is based on the wave-guided type circuit for intra-body communication [6]. An input signal form the signal generator is flowed in a palm through a pair of electrodes. On this occasion, an electric field is generated around the electrodes in the shallow part of the skin of a palm, and is subsequently stretched to another pair of electrodes; it is detected as a propagated signal by the receiver. We refer to the detected signal as an intra-palm propagation signal.

It is inconvenience for users to put electrodes on a palm every time measurement (authentication) is achieved. Thus, we prepared dedicated measuring devices as shown in Fig. 2.

Figs. 2a-2d are created by making plaster casts of palms and the electrodes are diverted from the metal (Ag/AgCl) parts of gel-padded disposal electrodes. The alignment of the electrodes in Fig. 2a is 2 cm in width and 5 cm in height. They are 4 cm by 5 cm, 2 cm by 3 cm, and 4 cm by 3 cm in the case of Figs. 2b-2d, respectively. The base of Fig. 2e is a mouse device for the computer, and cupper plates are used as electrodes. The alignment of the electrodes consists of a width of 2 cm and a height of 5 cm.

Using the dedicated measuring devices, we measured intra-palm propagation signals from 21 experimental subjects. A measurement scene is shown in Fig. 3.

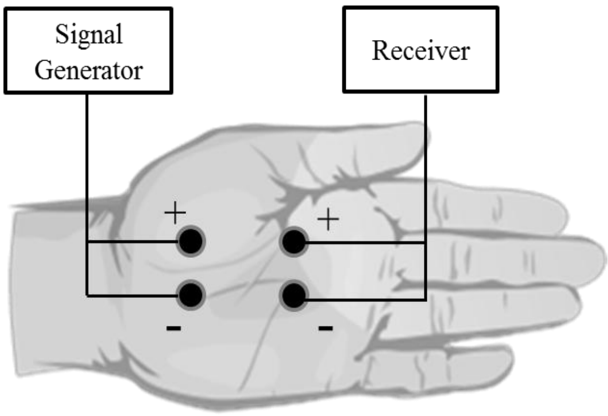


Fig. 1 Measurement of intra-palm propagation signals.

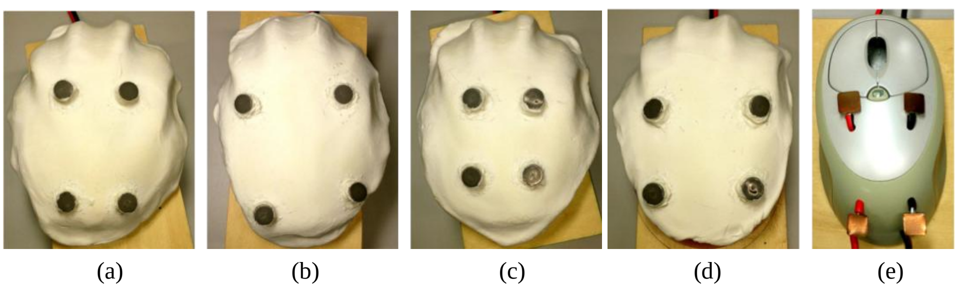


Fig. 2 Dedicated measuring devices for intra-palm propagation signals.

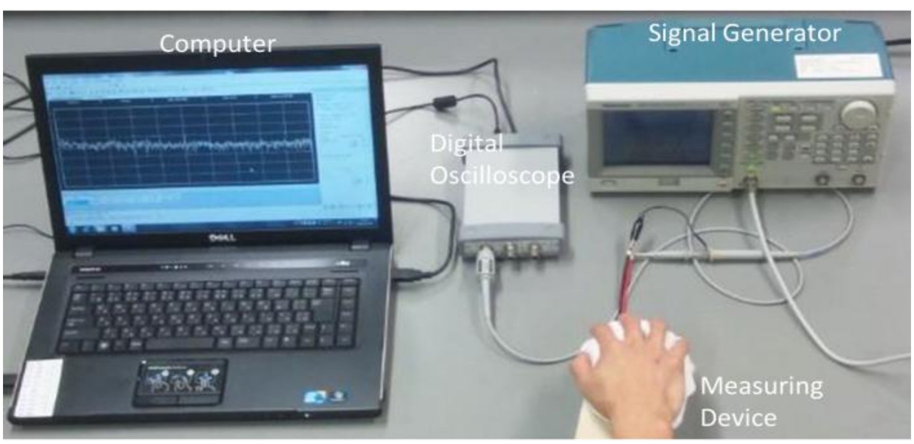


Fig. 3 A measurement scene using the dedicated measuring device.

The subjects sat on a chair and washed the stain from their palms. They put their palms on the dedicated measuring devices on and remained still. A pseudo white noise of 4 $V_{p\text{-}p}$ and 100 MHz bandwidth was output from the signal generator, intra-palm propagation signals were detected by the digital oscilloscope, of which the sampling rate was 1 G samples/s, and the signals were saved in the computer that was connected to the oscilloscope. The measurement was performed two times per day and repeated 30 times (days). As a result, sixty signals were collected from each subject.

3. Verification Using Intra-Palm Propagation Signals

We employ the amplitude spectrum of an intra-palm propagation signal as an individual feature. However, the spectrum is averaged and normalized to suppress intra-individual variation.

The averaging is achieved as follows: the saved data of a detected intra-palm propagation signal are equally divided into several parts, a DC component is removed from each part, an amplitude spectrum is calculated from each part using a FFT (fast Fourier transform), and an averaged spectrum is obtained by ensemble-averaging all amplitude spectra. The reason why DC components are removed is that the DC component becomes extremely large compared with other components; therefore, the similarity comparison of the spectra is dominated by only the DC component if it is not removed. The normalizing is achieved by equalizing the means of amplitude spectra from all users.

Two verification methods are tried in our studies. One is a method on the basis of Euclidean distance and the other is on the basis of SVM (support vector machine).

In the verification method using the Euclidean distance, the differences between spectral values at all frequency bins are accumulated [7].

$$\text{Distance} = \sqrt{\sum_{k=1}^{M}\left(t_k - v_k\right)^2} \tag{1}$$

Where t_k, v_k are the amplitude spectrum of a template and that of a verification signal, respectively. k is a frequency index, and M is the number of the frequency bins. The template is obtained by ensemble-averaging several amplitude spectra of each user in advance to verification. The distance is compared with a threshold. If the distance is smaller than the threshold, the user who presented the verification signal is regarded as a genuine user. This method is simple and achieved in low computational complexity; however, higher verification performance could not be performed.

The SVM is a strong classifier based on learning, of which the advantage over other classifiers, such as neural networks, is that the SVM has no local minimum problem [8].

Because a SVM is a two-class classifier, an ingenious scheme is required when the SVM is applied to multi-class classification. We use one versus one (1vs1) SVM, which constructs a learning model that compares a genuine user with another user [9]. The effect of 1vs1 SVM in verification has been already confirmed in our conventional studies [5].

Fig. 4 shows the verification procedure based on a 1vs1 SVM [10]. SVM models for all users of a system are constructed in the learning stage. Each model is learned by teaching to output “+1” for the intra-palm propagation spectra of a genuine user and “-1” for the intra-palm propagation spectra of another user.

In the verification stage, an applicant of the system presents a genuine user’s name, and his/her intra-palm propagation signal is measured one time. After smoothing, normalizing, and feature extracting, his/her intra-palm propagation spectrum is evaluated in learned models that are related to the specified genuine user. If the number of leaned models that output positive values is larger than a threshold, that is, based on the majority rule, the spectrum is considered

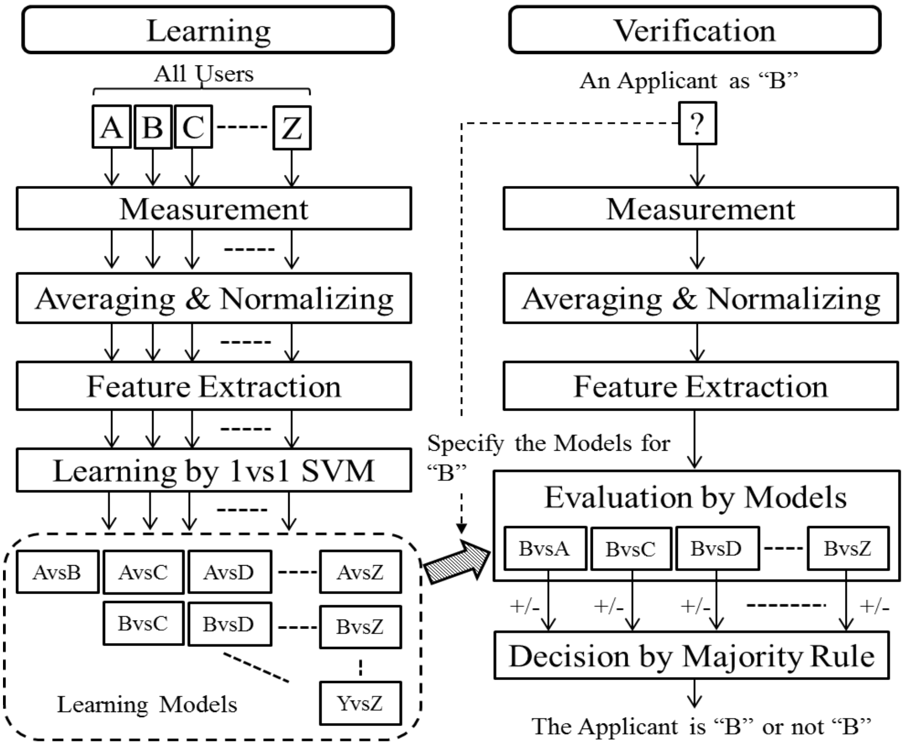


Fig. 4 **Verification procedure based on a 1vs1 SVM.**

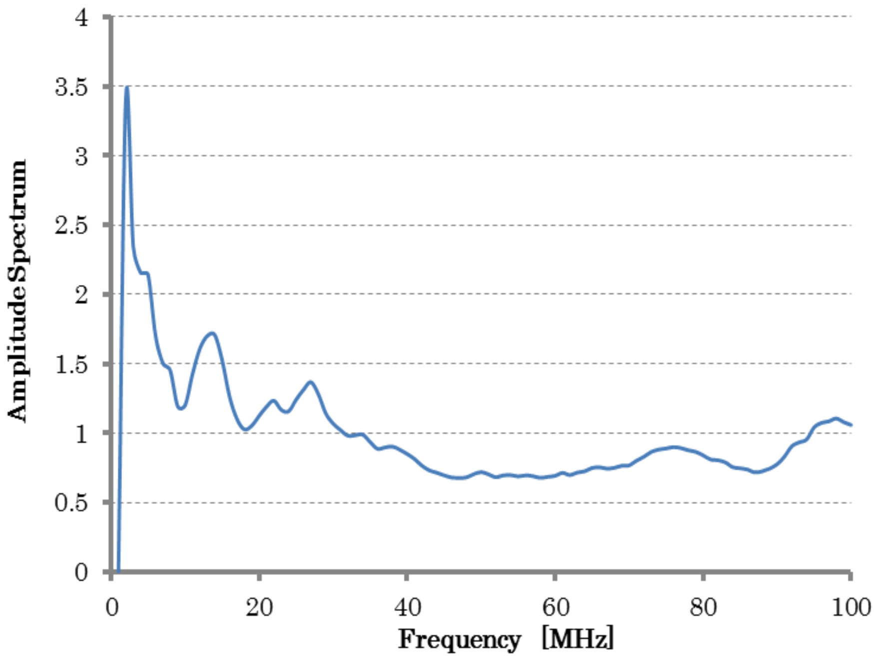


Fig. 5 **An example of the spectrum as an individual feature.**

to belong to the genuine user, and the applicant is accepted in the system.

4. Performance Evaluation

First, we evaluated the verification performance of the intra-palm propagation signals measured in Sect. 2 using Euclidean distance. Each individual feature was the spectral amplitudes for 100 frequency bins (dimensions). An example of the spectrum is shown in Fig. 5.

Five amplitude spectra from each experimental subject were used for generating a template. The remaining fifty-five spectra were used in performance verification. In addition, we adopted the LOO (leave one out) method in this evaluation. Only one subject is excluded, and the performance for the remaining users is evaluated. Although the LOO method is simple, it is generally used to evaluate the influence on performance by specific users.

The equal error rates (EERs) are shown in Table 1, wherein “None” represents the case in which the LOO method is not employed, that is, using all subjects.

The variance of EERs in each device is approximately 1%; therefore, it is confirmed that the verification performance of intra-palm propagation signals is not influenced by specific subjects (users). In other words, the database of intra-palm propagation signals used in this evaluation does not include anomalous subjects.

The EERs of (d) or (e) are slightly smaller than those of (a), (b) or (c). The reason is unclear but it is true that the verification performance depends on measuring devices.

It is clear that the verification performance on the basis of Euclidian distance is not very powerful. Thus, we evaluated the verification performance using SVM.

For each subject, 40 data (spectra) were employed for the learning of models; the remaining 20 data were used for verification. The spectral amplitudes for 100 frequency bins were equally divided into 10 parts and ten amplitude spectral values in the optimal part for each subject were used as an individual feature. The optimal part for each user and the optimal parameters for learning each SVM model were determined using grid searching (round-robin formula). The parameter ranges are summarized in Table 2.

Fig. 6 shows error rate curves: FRR (false rejection rate) and FAR (false acceptance rate). The horizontal axis corresponds to a threshold value of the majority rules.

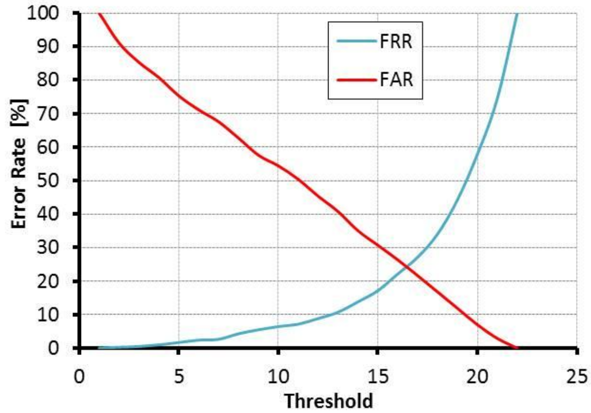
The EERs of (a), (b), (c), (d), and (e) are 24.2%, 25.2%,

Table 1 EERs (%) using LOO method in measuring devices (a)-(e).

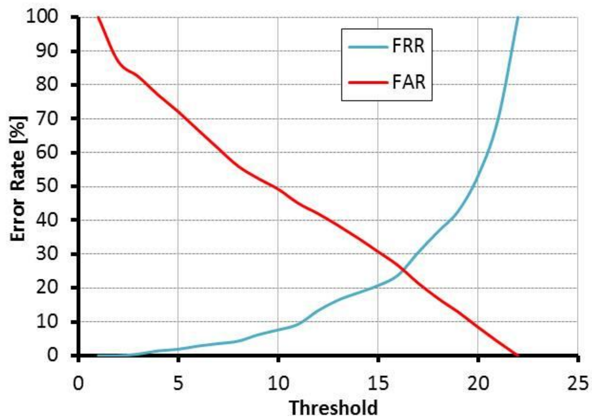
Excluded subject	(a)	(b)	(c)	(d)	(e)
A	48.7	48.1	48.8	45.9	45.9
B	48.8	48.0	48.7	45.9	45.7
C	49.1	48.2	49.0	46.3	46.8
D	48.8	47.9	48.9	45.7	45.7
E	48.6	47.8	48.5	45.4	45.8
F	48.7	48.0	48.8	46.0	46.0
G	48.6	48.3	48.9	46.2	45.9
H	49.2	48.7	49.5	46.7	48.2
I	48.5	47.9	48.7	45.5	45.7
J	48.6	48.2	48.8	46.0	45.7
K	48.6	47.9	48.5	45.9	45.9
L	48.6	48.3	48.7	46.2	45.8
M	48.7	47.9	48.8	46.1	45.8
N	48.5	47.8	48.6	45.2	45.6
O	48.8	48.2	48.8	45.9	45.4
P	48.6	48.4	48.6	46.1	45.8
Q	48.5	48.3	48.5	46.1	45.9
R	48.5	48.2	48.7	46.9	45.9
S	48.7	48.3	48.7	46.0	45.9
T	48.6	47.9	48.7	45.2	46.2
U	48.5	48.3	48.5	46.9	45.9
None	48.6	48.1	48.7	46.0	45.8

Table 2 Parameter ranges in the grid searching.

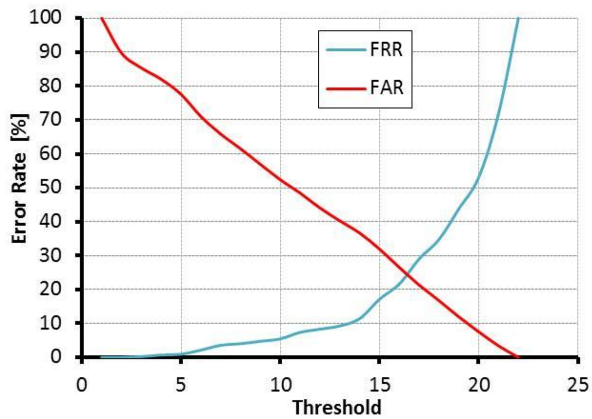
Cost parameter		0.001,0.002,…, 0.009, 0.010, 0.015,…, 0.095, 0.10, 0.15, …, 0.95, 1.0, 2.0, …, 9.0, 10.0
Kernel function	Polynomial: *d*	1, 2, 3
	RBF: δ	0.001, 0.002, …, 0.009, 0.010, 0.015, …, 0.095, 0.10, 0.15, …, 0.95, 1.0, 2.0, …, 9.0, 10.0



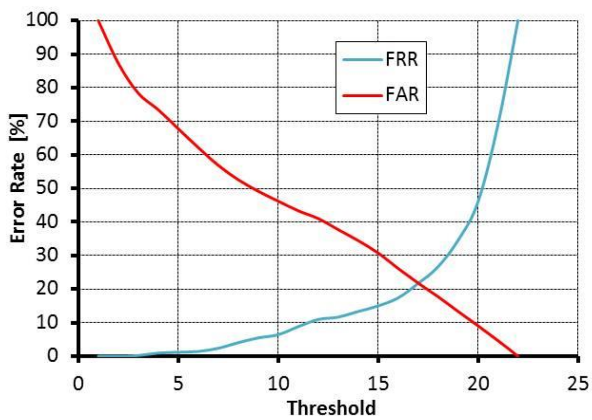
(a)



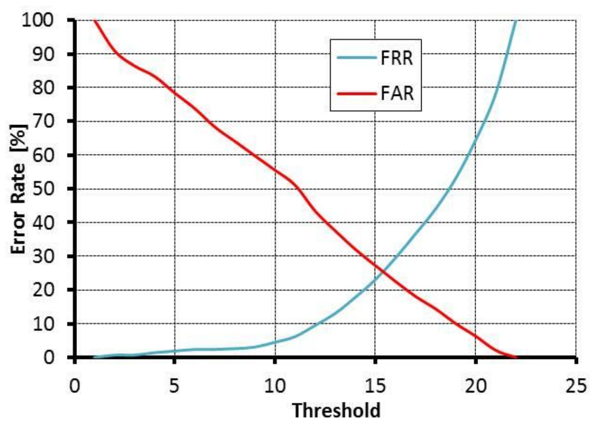
(b)



(c)



(d)



(e)

Fig. 6 Error rate curves in measuring devices (a)-(e).

24.1%, 21.7%, and 25.2%, respectively. Comparing with the case of using Euclidian distance, the EERs are greatly improved, and as a result the smallest EER of approximately 22% was obtained in the device (d). From this result, we consider that there is a possibility to use intra-palm propagation signals as biometrics.

On the other hand, even using SVM which is a powerful verification method, the above verification rates are insufficient to conclude that intra-palm propagation signals can be used as biometrics. This is caused by high FAR; therefore, it is necessary to suppress intra-individual variation. Not only that, all processes related to verification must be re-examined in the future.

5. Conclusions

We have investigated the use of intra-palm propagation signals as biometrics. In this paper, we prepared dedicated measuring devices, measured intra-palm propagation signals using them from twenty-one experimental subjects, and evaluated the verification performance on the basis of Euclidian distance or SVM. As a result, the possibility to use intra-palm propagation signals as biometrics was confirmed; however, it was also confirmed that further improvement of the verification performance was necessary.

In the performance evaluations, it was clear that the verification performance was influenced by measuring devices. Regarding the devices used in this paper, the influence from the contact stability between electrodes and a palm, the variation in electrode position on a palm, and the size of palms were not considered. We have already examined the effect of new measuring devices considering the above points [11].

Another issue is about an input signal. In this paper, a white noise was used as an input signal in order to efficiently obtain all spectral values. However, there might be the variation of spectral values in the white noise and it might increase intra-individual variation in intra-palm propagation spectra and degrade the verification performance. We are now examining the use of specified signals that consist of several sinusoidal waves with different phases. This scheme suppresses the intra-individual variation and may improve the verification performance.

Finally, increasing the number of experimental subjects to obtain reliable results is problematic.

References

[1] Altinok, A., and Turk, M. 2003. "Temporal Integration for Continuous Multimodal Biometrics." In *Proc. of 2003 Workshop on Multimodal User Authentication*, 131-7.

[2] Nakanishi, I., Baba, S., and Miyamoto, C. 2010. "On-demand Biometric Authentication of Computer Users Using Brain Waves." *Part I, CCIS* 87: 504-14.

[3] Nakanishi, I., Yorikane, Y., Itoh, Y., and Fukui, Y. 2007. "Biometric Identity Verification Using Intra-Body Propagation Signal." In *Proc. of 2007 Biometrics Symposium.*

[4] Nakanishi, I., and Sodani, Y. 2010. "SVM-Based Biometric Authentication Using Intra-Body Propagation Signals." In *Proc. of 2010 7th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS2010)*, 561-6.

[5] Nakanishi, I., Sodani, Y., and Li, S. 2013. "User Verification Based on the Support Vector Machine Using Intra-Body Propagation Signals." *International Journal of Biometrics* 5 (3/4): 288-305.

[6] Hachisuka, K., Nakata, A., Takeda, T., Siba, K., Sasaki, K., Hosaka, H., and Itao, K. 2002. "Development of Devices for Communication through Human Bodies (in Japanese)." *Micromechatronics, Bulletin of the Horological Institute of Japan* 46 (2): 53-64.

[7] Inada, T., Nakanishi, I., Sodani, Y., and Li, S. 2012. "Biometric Authentication Using Intra-Palm Propagation Signals." In *Proc. of International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC 2012).*

[8] Cristianini, N., and Shawe-Taylor, J. 2000. *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods.* Cambridge, UK, Cambridge University Press.

[9] Hsu, C., and Lin, C. 2002. "A Comparison of Methods for Multiclass Support Vector Machines." *IEEE Trans. Neural Networks* 13 (2): 415-25.

[10] Nakanishi, I., Inada, T., and Li, S. 2013. "Performance Evaluation of Intra-Palm Propagation Signals as Biometrics." In *Proc. of 2013 International Conference*

on Biometrics and Kansei Engineering (ICBAKE 2013), 91-4.

[11] Nakanishi, I., Inada, T., and Li, S. 2014. "New Dedicated Measuring Devices for Intra-Palm Propagation Signals." In *Proc. of 2014 International Symposium on Biometrics and Security Technologies (ISBAST 2014)*, 35-8.