Performance Evaluation of Intra-Palm Propagation Signals as Biometrics

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***Abstract*—The use of intra-palm propagation signals as biometrics is proposed. The intra-palm propagation signal is an electromagnetic wave propagated in the palm. In this study, intra-palm propagation signals are measured using dedicated measuring devices and their verification performance based on the Support Vector Machine is evaluated using twenty-one subjects. The equal error rate is approximately 25 %.**

***Keywords*-biometrics; intra-palm propagation signal; SVM**

I. Introduction

Almost all of biometric modalities are studied as an alternative to a conventional authentication method such as the password or the ID card. However, there are applications in which the conventional method is unusable.

One of the applications is user management, in which successive authentication such as continuous authentication [1] or on-demand authentication [2] is required. Users are required to present their biometric data successively; therefore, the password and the ID card are inapplicable. In such an application, only the biometrics is applicable. However, not all biometric modalities are usable. Only the modalities that make it possible to present biometric data transparently are applicable.

Considering the situation of user management, it is imaginable that users are controlling a system while griping or touching something of the system such as a handle of a vehicle or a mouse device of a computer. In such a case, palms are an interface between the system and the users. Thus, we have proposed to use intra-palm propagation signals as transparent biometrics [3].

We confirmed that intra-palm propagation signals were measurable by using the proposed measuring system and surely propagated in palms. However, the verification performance based on the Euclidian distance was very low. In this study, we introduce the support vector machine (SVM) into the verification stage in order to improve the verification performance. The effectiveness of the SVM had already confirmed in Ref. [4].

In Sect. II, we explain about the measurement of intra-palm propagation signals. Next, we introduce the feature extraction and verification method in Sect. III. The verification is performed based on the SVM. In Sect. IV, the verification performance of intra-palm propagation signals is evaluated in the experiments using twenty-one subjects. Finally, the concluding remarks are presented in Sect. V.

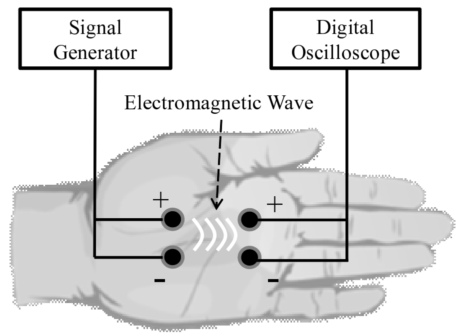


Figure 1. The measuring system of intra-palm propagation signals.

II. Measurement of Intra-Palm Propagation Signals

A. Intra-Palm Propagation Signal

Figure 1 shows a basic structure of the measuring system of intra-palm propagation signals. It is based on the wave-guided type circuit for intra-body communication [5]. An input signal form a signal generator is flowed in a palm through a pair of electrodes. On this occasion, a weak electromagnetic wave is leaked and then propagated to another pair of electrodes. The propagated signal is detected and then recorded by a receiver such as a digital oscilloscope.

B. Dedicated Measuring Devices

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

The left side one is made by making a plaster cast of a palm and the electrode is diverted form the metal part of a gel-padded disposal electrode. The base of the right side one is a mouse device and cupper plates are used as electrodes. The alignment of the electrodes in both devices is 5 cm length and 2 cm width.

(a) Plaster cast type

(b) Mouse device type

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

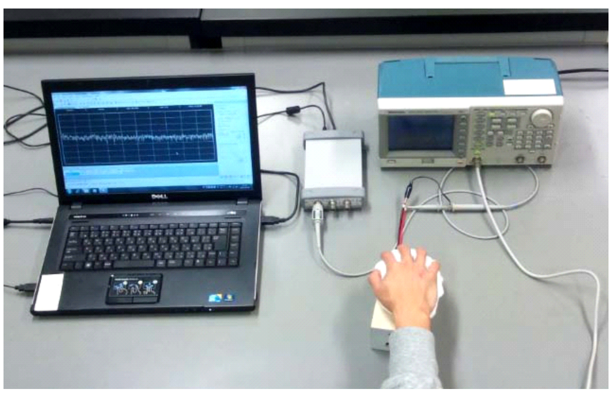


Figure 3. A measurement scene using the dedicated measuring device.

C. Measurement

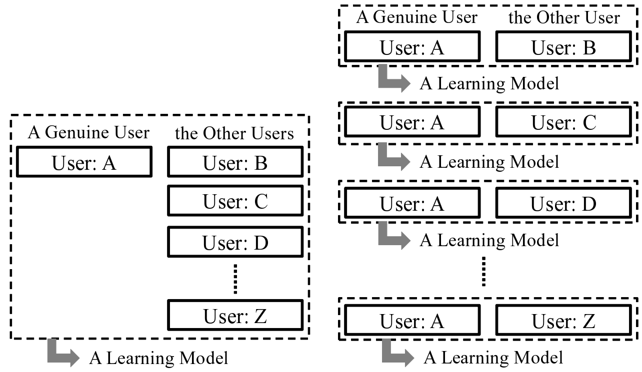
By using the dedicated measuring devices, we measured intra-palm propagation signals from twenty-one subjects. The measurement was done twice on a day and repeated 30 times (days). A measurement scene is shown in Fig. 3. An input signal from the signal generator was a pseudo white noise of 4 V_{p-p} and 100 MHz bandwidth.

The subjects sat on a chair and washed out stain on thier palm. After that, they put their palms on a dedicated measuring device and kept themself at rest. In the meantime, intra-body propagation signals were measured by the digital oscilloscope of which sampling frequency was 200 MHz and then saved in a computer.

III. Verification Using Intra-Palm Propagation Signals

A. Feature Extraction

In this study, the amplitude spectrum of an intra-palm propagation signal is used as individual feature. However, in order to suppress intra-individual variation, the spectrum is averaged and normalized. The averaging is achieved as follows: measured intra-palm propagation data are equally divided into several parts, an amplitude spectrum is obtained from each part, and an averaged spectrum is obtained by ensemble-averaging all amplitude spectra. The normalizing is achieved by equalizing the means of all amplitude spectra.



(a) 1vsALL SVM

(b) 1vs1 SVM

Figure 4. Comparing of the balance of learning data between 1vsALL SVM and 1vs1 SVM.

B. Verification Based on SVM

In Ref. [3], the verification performance of intra-palm propagation signals was evaluated based on the Euclidean distance between the spectral values at each frequency bin but it was not so high to confirm that the intra-palm propagation signal has the ability to be a new biometric modality.

In this paper, the Support Vector Machine (SVM) [6] is introduced into the verification. The SVM is a strong classifier based on learning, of which advantage over other classifiers such as neural-networks is that the SVM has no local minimum problem. However, the SVM is basically two-class classifier; therefore, if the SVM is simply applied in multi-class classification (one versus all SVM: 1vsALL SVM), the unbalance of learning data is caused as (a) in Fig. 4, where the solid-line box indicates the learning data for each user and the dashed-line box presents a learning model. The unbalance of learning data brings the degradation of verification performance. Therefore, some ingenious scheme is required when the SVM is applied in verification.

As one of the schemes, we introduce the one versus one (1vs1) SVM [7], which constructs a learning model comparing a genuine user with the other (another) user. The 1vs1 SVM resolves the unbalance problem shown as (b) in Fig. 4. On the other hand, the 1vs1 SVM needs many learning models and a final decision rule for considering the

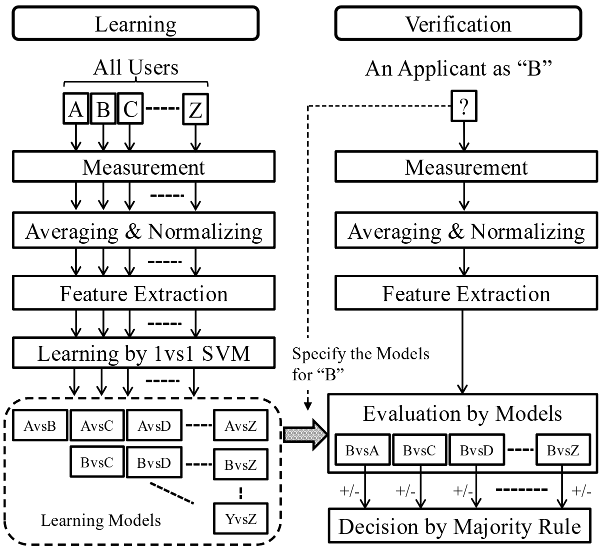


Figure 5. Verification procedure based on 1vs1 SVM.

results from the models corresponding to a genuine user. In this study, we use the majority rule.

Figure 5 shows the proposed verification procedure based on 1vs1 SVM for the intra-palm propagation signal. For all users of a system, models 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 those of another user.

In the verification stage, firstly, an applicant of the system presents genuine user's name and then his/her intra-palm propagation signal is measured once. After smoothing, normalizing, and feature extracting, the intra-palm propagation spectrum is evaluated in all models corresponding to the genuine user. Then if the number of the models that output positive value is larger than a threshold, that is, based on the majority rule, the spectrum is regarded as of the genuine user and the applicant is permitted to use the system.

IV. Verification Experiments

A. Conditions

In order to evaluate the verification performance of the intra-palm propagation signal based on the 1vs1 SVM, we carried out the verification experiment using the intra-palm propagation signals measured in Sect. II.

SVM^{light} [8] was used as SVM tool kit. Forty data (spectra) from each subject were used for the learning of models and the rest twenty data from each subject were used for verification.

The spectral amplitudes at one hundred frequency bins (dimensions) were obtained by the FFT and then they were equally divided into ten parts. In this experiment, ten amplitude spectral values in the optimal part for each user (subject) were used as individual feature. Not only the optimal part of the frequency band but also the optimal parameters for the SVM were found by using the grid searching, that is, round-robin formula. The parameter ranges are summarized in Table I.

Table I
Parameter ranges in the grid searching.

Cost Parameter		0.001, 0.002, $\cdots$, 0.009, 0.010, 0.015, $\cdots$, 0.095, 0.10, 0.15, $\cdots$, 0.95, 1.0, 2.0, $\cdots$, 9.0, 10.0
Kernel Function	Polynomial: d	1, 2, 3
	RBF: δ	0.001, 0.002, $\cdots$, 0.009, 0.010, 0.015, $\cdots$, 0.095, 0.10, 0.15, $\cdots$, 0.95, 1.0, 2.0, $\cdots$, 9.0, 10.0

B. Results

Figure 6 shows error rate curves: False Rejection Rate (FRR) and False Acceptance Rate (FAR). The horizontal axis corresponds to a threshold value in the majority rule. From these results, it is confirmed that the Equal Error Rate (EER) was approximately 25 % without relation to the shape and the material of devices.

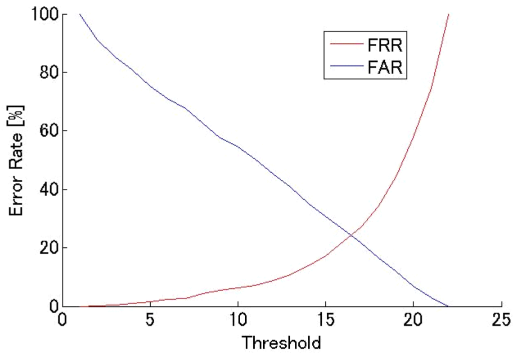
Even using the SVM as a powerful verification method, the verification rate was not so high yet. Therefore, it is necessary to reexamine the measuring method of intra-palm propagation signals and the feature extraction method from them. For instance, a white noise was used as an input signal in order to obtain all spectral values efficiently. However, the variation of the spectral values of the white noise is larger and then it might increase intra-individual variation in the intra-palm propagation spectrum and degraded the verification performance. In addition, using the white noise made impossible to use the phase information of propagated signals.

We are now examining the use of a specified signal that consists of several sinusoidal waves with different phases. This scheme suppresses the intra-individual variation and increases the dimension of an individual feature. Therefore, the verification performance may be improved.

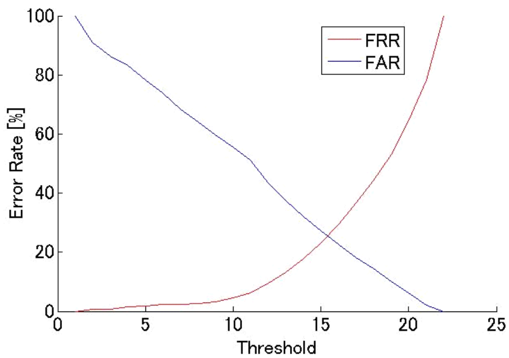
V. Conclusions

We have proposed the use of intra-palm propagation signals as biometrics. However, the verification performance of the conventional method was low. Thus, we introduced the SVM into the verification stage and evaluated the verification performance. As a result, we obtained the EER of approximately 25 % among twenty-one subjects.

There are some problems to be studied further. Reexamination of methods for measuring of intra-palm propagation signals and feature extracting from them is necessary in order to achieve higher verification rate. In addition, the



(a) Plaster cast type



(b) Mouse device type

Figure 6. Error rate curves.

number of subjects must be increased for improving the reliability of the results obtained in the experiments. Moreover, it is confirmed that the variation of the electrode position on a palm influences on verification performance. Therefore, a new structure of the measuring device is required for stabilizing the electrode position.

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