Evaluation of the Brain Wave as Biometrics in a Simulated Driving Environment

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***Abstract*—In the case of user management, continuous or on-demand biometric authentication is effective for achieving higher security with a light system load. However, it requires us to present biometric data unconsciously. In this paper, we focus attention on the brain wave as unconscious biometrics. In particular, assuming driver authentication, we measure the brain waves of drivers when they are using a simplified driving simulator. We evaluate verification performance using 23 subjects and obtain the EER of about 20 %.**

I. Introduction

Biometric person authentication gains public attention. It is well known that the fingerprint and the iris achieve higher security and they are already used in security systems [1]. On the other hand, it was reported that authentication systems using them were circumvented by using fake fingers or printed iris images [2], [3]. The reason is that the fingerprint or the iris are appeared on a body surface and so become observable by using easily obtainable sensors.

The vein is contained within the body; therefore, it is expected to have tolerability to the circumvention. However, it is also reported that even authentication system using the vein accepted artifacts in enrollment and verification [4]. This is due to lack of the function of liveness detection that examines whether an object is a part of a living body. The liveness detection scheme is necessary for protecting biometric authentication systems from spoofing using artifacts.

On the other hand, conventional biometric systems mainly assume applications based on one-time-only authentication such as access control, banking, passport control, and so on. However, from the viewpoint of user management, the one-time-only authentication is low-security. After initially authenticating a genuine user, a system cannot detect spoofing by an imposter who has replaced the user.

Assuming that both authentication and application execution are simultaneously achieved in a single system, the one-time-only authentication is not a heavy load on the system since the authentication is performed only once at the start of the application execution while security is not guaranteed after the authentication.

In order to cope with this problem, continuous authentication is proposed [5], [6]. The security is guaranteed all the while that the application is executed but the continuous authentication brings a heavy load to the system. In fact, it was reported that the overhead for the continuous authentication was 42 % in Ref. [6].

Thus, we have proposed on-demand authentication in which users are authenticated on a regular schedule or a nonregular one on demand of authentication from the system [7]. The on-demand authentication makes the system load lighter.

By the way, the fingerprint and the iris are not suitable for the continuous and the on-demand authentication because they ask users to present biometric data whenever the users are authenticated. In other words, the continuous and the on-demand authentication need the biometrics that is able to present biometric data unconsciously. As such unconscious biometrics, the face, ear, voice, keystroke and gait are applicable but the face and the ear are easily imitated using artifacts, and the voice, keystroke and gait limit the use of biometric applications.

It has been proposed to use brain waves as the biometrics [8]–[19]. The brain wave is generated by activities of neurons in the cerebral cortex; therefore, it is contained within the body, thereby preventing circumvention of security. Of course, the brain wave is generated by only live human beings. If the liveness can be detected using the brain wave, no additional sensor is needed for the liveness detection. Moreover, the brain wave is generated autonomously and unconsciously; therefore, it enables on-demand authentication. Conversely, brain waves are not suitable for one-time-only authentication since users are required to put sensors on their scalp every time they are authenticated. From the viewpoint of accessibility, the brain wave as biometrics is the most adequate.

Based on the above facts, we believe that operator verification of a system such as a computer and a vehicle is suitable for the authentication using the brain wave [7], [20]. Operators wear a brain wave sensor and they are verified on demand while using the system as illustrated in Fig. 1. For instance, in remote education systems, students should be authenticated while learning. It is even more so for students who are trying to obtain some academic degree or public qualification. In addition, operators of public transportation systems should be authenticated while operating the systems since hundreds of

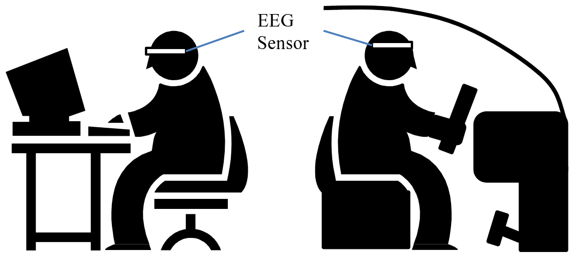


Fig. 1. Illustrations of on-demand operator verification using the brain wave.

human lives depend on them. There are other examples: pilots of aircrafts, drivers of emergency vehicles, and operators of military weapons.

In Ref. [20], we measured brain waves of drivers who were tracing routes as mental task and evaluated the verification performance. However, the route tracing did not require them to move their four limbs. For evaluating the verification performance in more practical environment, some actual task that involves four limbs' moving should be assumed. In this paper, we examine the verification performance of the brain waves of drivers who are using a simplified driving simulator.

II. Authentication Using Brain Waves

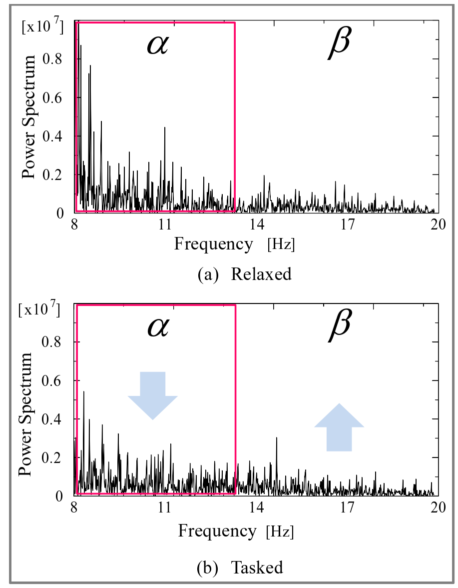
A. Brain Wave

Electrical changes from large number of synapses (neurons) in the cerebral cortex are accumulated and then detected as a brain wave (Electroencephalogram: EEG) on the scalp by using an electrode. Because of spatiotemporal dispersiveness of the neurons, there are not distinct patterns in the EEG in general. However, when activity of the cerebral cortex becomes low, brain waves partially become synchronous and thereby some distinctive pattern is observed. As such patterns, δ (0.5-3Hz), θ (4-7Hz), α (8-13Hz), and β (14-30Hz) are well known and detectable when human beings are during deep sleep, getting sleepy, relaxed with closed eyes, and in some mental activity, respectively. In particular, the α and/or the β waves are applicable for person authentication.

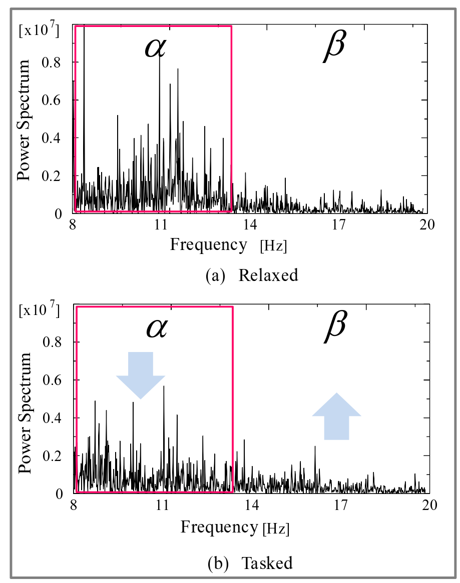
B. Feature Extraction and Verification

In order to actualize the authentication using EEGs, the architecture for feature extraction and verification must be as simple as possible. Therefore, we have used a single sensor for detecting the brain wave and had proposed to extract power spectra at the α-β band as individual features and a verification method based on the difference between a mean value of the power spectrum in a mental-tasked condition and that in a relaxed condition [20]. This concept is based on the fact that α waves are detectable and β waves are undetectable in the relax condition while the α waves are suppressed and the β waves become detectable in the mental-tasked condition as shown in Fig. 2, which describes the spectra at the α-β band in the relaxed and the mental-tasked conditions from two subjects.

However, the conventional method needed additional measurement in the relaxed condition. It was inconvenience for users in practical applications. In this paper, we propose to compare spectra directly in the tasked condition. Additionally, for suppressing intra-individual variation, we introduce normalization into verification.



(a) Subject: A



(b) Subject: B

Fig. 2. Examples of the EEG spectrum from two subjects.

Furthermore, we divide the α-β band into several partitions and fuse scores from all partitions [20]. Figure 3 illustrates the partitioning, where the number of partitions is four. The reason why we introduce the partitioning is that the spectral

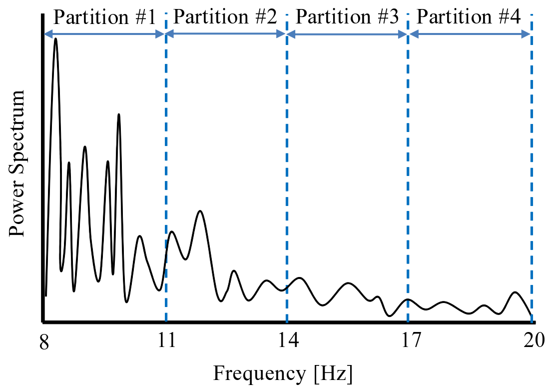


Fig. 3. Partitions in the α-β band.

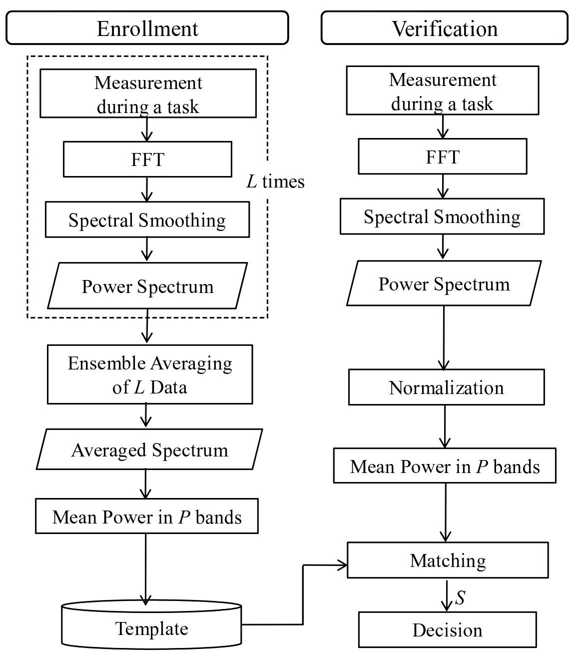


Fig. 4. The block diagram of authentication.

distribution at α-β band depends on an individual; therefore, each partition has different effect on verification.

The block diagram of authentication is described in Fig. 4. In advance of the verification stage, the enrollment of templates is carried out. A brain wave is measured in a tasked condition and then its power spectrum is calculated using the FFT. For suppressing the variation of spectral values, moving average of which window size is five is performed and thereby we obtain a smoothed power spectrum. From each user, the above process is repeated L times and then using the L spectra, we obtain an ensemble-averaged spectrum. After that, mean values of the spectrum are calculated in all partitions and then stored as templates.

In the verification stage, an EEG of an authenticated user is measured in a tasked condition and processed in the same way as in the enrollment stage. After normalization, a verification

Fig. 5. A still image of the driving scene.

score S is calculated by

$$S = \sum_{p=1}^{P} |s_T^t - s^t|_p. \tag{1}$$

where P is the number of partitions, s_T^t is a template, and s^t is a mean value of each partition. For normalization, each power spectral value of s^t is multiplied by a ratio of a mean value of all power spectra of a template: s_T^t to that of s^t. The mean power spectrum of s^t is equalized to that of the template: s_T^t.

If S is less than a threshold, the user is authenticated genuine.

III. Experiments

Experiments in practical driving carry a risk of having some accident. There is a way to introduce a special training simulator that is possible to simulate the driving in our laboratory but it has also an issue of cost. Therefore, we adopted a simplified driving simulator that was composed of gaming machines.

A. Simplified Driving Simulator

Driving scenes were generated by the PlayStation 3 (PS3) as hardware and the Gran Turismo 5 Prologue (GT5P) as software produced by Sony Computer Entertainment Inc.. However, the GT5P was a racing game and so the following settings were applied to utilize it as a driving simulator.

- Set a manual transmission to the first gear to limit the maximum speed of a car to 65 km/h
- Set a driving course to an urban road in London to drive the car in a general road
- Set a racing mode to time trial, that is, solo drive to avoid accidents with other cars

A still image of the driving scene is shown in Fig. 5.

The driving scenes were displayed on a 60-inch screen and the size was 1100 mm by 830 mm. The distance between the screen and a subject was 1300 mm. These had been pre-liminary determined using nine subjects based on evaluation

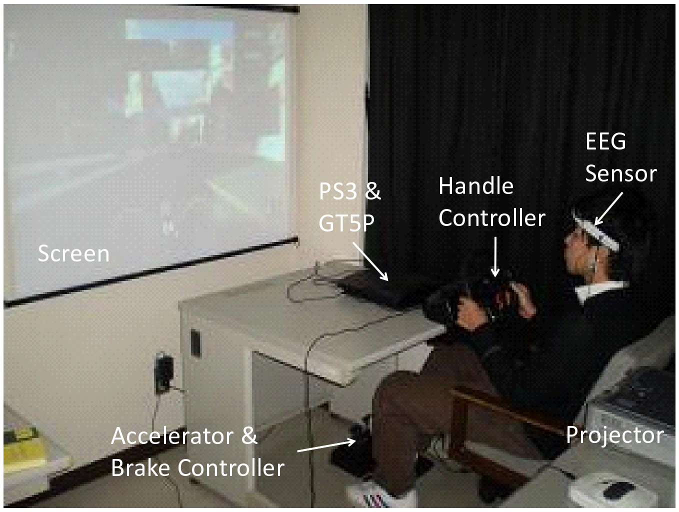


Fig. 6. A measurement scene of brain waves using the simplified driving simulator.

how views from the subjects were similar with practical ones. A handle, accelerator and brake were equipped by imitated controllers: Driving Force GT produced by Logitech. Figure 6 shows a measurement scene.

B. Measurement of Brain Waves

We used a consumer single-channel electroencephalograph as an EEG sensor. By using a headband, a single electrode (sensor) was set on the frontal region of head which corresponded to the frontal pole (Fp1) defined by the international standard: 10/20 method [21]. The specifications are summarized in Table I.

TABLE I
SPECIFICATIONS OF THE BRAIN WAVE SENSOR USED.

Frequency Range	1-24 Hz
Minimum Voltage	5 μV_{p-p}
Maximum Voltage	80 μV_{p-p}
Sampling Frequency	128 Hz

The number of subjects was 23. All were males around 20 years old and each had a driver's license. Before measurement, the subjects were required to make two rounds to adapt themselves to maneuvering feeling. After the practice, the subjects wore the sensor and their brain waves were measured while handling the controllers depending on driving scenes. If there was some accident, for instance, their car hit against a wall, the measurement was redone.

Each measuring time was three minutes. The measurement was carried out once a day and it was repeated ten times (days) at an interval of at least one week. Resultingly, 10 EEGs were obtained from each subject.

IV. EXPERIMENTAL RESULTS

Middle one-minute data of each measured EEG were used in experiments. The average number L was set to five, that is to say, five EEGs of each subject were used for generating his templates. In the verification, the rest five data of each subject were used as those of a genuine user and all other subjects' data were used as those of imposters.

Verification performance is evaluated by using the equal error rate (EER) where the false acceptance rate (FAR) is equal with the false rejection rate (FRR). The EER was 23 % in the case of four partitions and it was 20 % in six partitions.

For reference, in Ref. [19], the verification performance of brain waves was evaluated assuming that subjects were under eye-closed and relaxed condition and the EER was about 11 %. Comparing the result with the above results, it is confirmed that the EER in the actual-tasked condition becomes larger than that in the relaxed condition. It is known that the α wave is dominantly detected in the relaxed condition while the β wave becomes dominant in the tasked condition. Such a difference might bring degradation of verification performance.

In order to know the influence of frequency band used in the verification, we examined the EER at each partition. Results are summarized in Table II. It is clear that the partitions at higher frequency band bring smaller EERs. The higher partitions correspond to the β band. As mentioned above, the β wave becomes dominant in the tasked condition. Therefore, to except lower partitions may improve the verification performance. Thus, we evaluated the performance using the scores from higher three partitions. As a result, the EER became 22 % and 25 % in the cases of four and six partitions, respectively. In the case of four partitions, the EER was slightly improved comparing with the case using all partitions. However, the EER in the case of six partitions was inversely degraded. The reason is not clear but it may be partly because the number of subjects in the experiments is quite small. For improving the verification performance, we must carefully examine the spectral characteristic at the β band to obtain more effective extraction method of individual features.

TABLE II
EERS AT EACH PARTITION

4 Partitions (Hz)	EER (%)
8-11	36
11-14	29
14-17	28
17-20	27
6 Partitions (Hz)	**EER (%)**
8-10	37
10-12	34
12-14	30
14-16	30
16-18	27
18-20	27

V. CONCLUSIONS

In this paper, we focused attention on brain waves as unconscious biometrics. In particular, assuming driver authentication, we measured the brain waves of drivers when they were using a simplified driving simulator. We extracted the power spectrum at α-β band as an individual feature and proposed a verification method based on similarities of the features. In addition, we divided the α-β band into four or six partitions and fused sub-scores from the partitions. As a result of experiments using 23 subjects, we obtained the EER of about 20 %.

There are many problems left to conclude that the brain wave is applicable to the driver authentication. There might be some difference between the brain waves using the simplified driving simulator and those in practical driving. The verification performance is not high enough; therefore, it is needed to adopt more powerful verification method such as the support vector machine (SVM). Of course, the number of subjects for experiments is quite small. Not only to increase the number of subjects but also to consider their age and occupation composition will be necessary when the applicability of brain waves to the driver authentication is confirmed on some level.

In the future, we are planning to develop an on-demand authentication system using the brain wave. It will be possible to evaluate performance of not only verification but also usability.

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