Personal Identification Using a Ballistocardiogram During Urination Obtained from a Toilet Seat

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Abstract Many sensors have been developed to measure physiological information in the toilet for health-care management and disease prevention. These sensors require personal identification to classify toilet users, assuming that several people use the same toilet. We aimed to provide biometrics based on cardiovascular physiological information obtained from a toilet seat. An electrocardiogram was measured by the toilet seat, and personal identification was performed, as in the previous study. In this study, we developed a ballistocardiographic (BCG) monitoring system using two vibration sensors installed beneath a toilet seat. We recorded 70 BCGs from seven healthy males during their urination. Peaks H, I, J, K, and L of the BCGs were clearly obtained. Twenty-six features such as amplitude and interval were calculated from the BCG peaks. Personal identification was performed using the Mahalanobis distance, and the accuracy of identification and equal error rate (EER) were calculated. The average identification accuracy was found to be 92.2%, and the average EER was found to be 34.1%. Although the EER was not sufficiently low, the average accuracy suggested that the proposed method using a toilet seat could provide adequate biometrics for application in the healthcare system.

Keywords: personal identification, urination, ballistocardiogram, toilet seat.

1. Introduction

Keeping track of physiological data in daily life can contribute to maintaining good health, increasing life expectancy, and improving the overall quality of life. Previously, patients were burdened with going to hospitals to undergo physiological evaluations. This inconvenience is alleviated by developing devices that are capable of performing the same physiological tests in the patient’s home. However, these devices have presented some problems that make it difficult for users to operate them and record the data by themselves. Keeping the devices clean is also a challenge for users, especially when the measurement involves biohazardous materials, such as excrement or blood. With these issues in mind, devices that can be fitted to a regular toilet have been developed, and these can automatically record physiological information in a user’s daily life. For example, previous studies have reported a system that measured blood pressure through a toilet seat [1], a system that measured voided volume without contacting urine [2], and a system that measured urine concentrations [3]. As these systems automatically measure physiological information, they do not require any additional action on the part of the toilet user, and they can collect data over an extended period of time. However, the data obtained from these systems is only reliable if the device can differentiate multiple users of the same toilet. For this reason, a personal identification function must be installed into the toilet systems.

Symax Inc. (Tokyo, Japan) has developed a service that allows toilet users to collect personal urine statistics and urinalysis results by simply installing a sensor inside their household toilet [4]. In a study conducted by Symax Inc., participants were assigned identification cards and the volume of excreted urine for each individual was automatically recorded over the period of observation. Automatic personal identification methods using fingerprint recognition [5, 6] and vein pattern recognition [7] are available, but these methods require the toilet user to participate actively in providing their biometrics to the sensor. Although analprint [6] or facial recognition [8] using
a camera does not require any action on the part of the toilet user, it is doubtful whether all toilet users would accept that a camera be installed in the toilet. Because a user is expected to use the toilet several times a day, biometrics that recognize features in their natural position and usual movements while using the toilet are ideal for personal identification. Sugimoto et al. [9] focused on walking, since that is a natural motion that most users perform on the way to the toilet. They carried out personal identification using the floor vibration waveform produced by the user walking. The average accuracy of personal identification results using this method was 92%. Unfortunately, the vibration waveform used in this personal identification sample did not include excretion. Furthermore, Kurahashi et al. [10] focused on the natural motion of pulling the toilet paper roll in the toilet and performed personal identification using the features obtained by a gyroscope installed inside the toilet paper core. The average accuracy of personal identification using this motion was 83.9% in the experiment without excretion, and was 69.2% in the experiment with excretion. Although biometrics for use in a toilet are needed, this function is still in the research phase, and a more accurate personal identification technology has yet to be developed.

We aimed to provide biometrics using cardiovascular data obtained through the toilet seat. In previous reports [11, 12], we performed personal identification using an electrocardiogram (ECG). The diffusion rate of a self-warming toilet seat with bidet function in Japan was 80.4% in 2019 [13], and such toilet seats are expected to be increasingly common in the future. We attached electrodes to a self-warming toilet seat to measure the user’s ECG. However, loud, intermittent noises interfered with the ECG measurement. The noises were thought to be caused by the heating element in the toilet seat. In the present study, we measured ballistocardiogram (BCG) instead of ECG to avoid the intermittent noises. A BCG forms part of the cardiovascular physiological information that describes the mechanical characteristics of a pumping heart and has peaks at G through O [14]. Because the BCG is a measurement of mechanical properties, it is robust against electrical noise. Therefore, stable waveform detection and identification are expected. A few identification results using BCG have been reported [15, 16]. These studies achieved personal identification using BCG during standing on the floor tile and sitting on the chair, with average accuracy of 96.2% and 100%, respectively. These studies have shown that BCG can be used for personal identification, but personal identification was not performed during urination. In this study, we attempted to achieve personal identification using the BCG recorded from a toilet seat during urination. We report the methodology in this paper to show the basic identification performance of toilet seat BCG.

2. Methods

2.1 BCG monitoring system from toilet seat

Figure 1 shows an outline of the BCG and ECG monitoring systems. The BCGs were measured using two vibration sensors (piezoelectric sensor, TDK Corp., Japan) installed beneath a toilet seat (TCF8PK22 #SC1, TOTO Ltd., Japan). The BCGs were recorded using DC signal transmitters (ZB-152H, Nihon Kohden Corp., Japan) and a multi-telemeter system (WEB-1000, Nihon Kohden Corp.). The BCGs were transmitted to a PC with a 30-Hz high-cut filter (7-th order Bessel filter) at a sampling frequency of 1 kHz. This system was installed in a man’s toilet at the University of Toyama, and the BCGs were recorded during urination. In addition, a chest ECG (CM4 lead), as reference data for the BCGs, was recorded simultaneously using an ECG transmitter (ZB-151H, Nihon Kohden Corp.) with the same multi-telemeter system.

2.2 Ethics and subject

The experimental protocol of this study was approved by the Ethics Committee of the University of Toyama (No. R2019052). Seven healthy males (aged 23.0 ± 0.8 years) participated in the study. When the subjects felt the need to urinate, they went to the toilet and urinated in a seated position. During urination, BCGs and ECGs were simultaneously measured from the time the subject sat on the toilet seat to the time he stood up. The BCGs during urination were recorded 10 times for each subject between October 1 and December 3, 201X. Since the BCG measurement was performed only once a day for each subject, BCG measurements for 10 urinations required a period of 10 to 40 days, depending on the individual. The duration of the data used for identity verification was 20 seconds or more. Because the length of time each subject sat on the toilet seat was different, 15 to 50 heartbeats were obtained. As a result, the number of registered heartbeats varied among individual subjects as well as...
within individual measurements. The voided volume was estimated from the weight difference before and after urination using a bathroom scale (DP-7800PW, Yamato Scale Co. Ltd., Japan) at each measurement. The bathroom scale measured changes in body weight with a resolution of 20 g.

### 2.3 Features for personal identification

Peaks H, I, J, K, and L were detected from the BCG using the following procedure. The maximum value of the BCG wave within 0.3 s after the ECG R-peak was identified as the J-peak [17]. The minimum value of the BCG wave between the ECG R-peak and the J-peak was identified as the I-negative-peak. The minimum value of the BCG wave between the J-peak and the ECG T-peak was identified as the K-negative-peak. The maximum value of the BCG wave between the ECG R-peak and the I-negative-peak was identified as the H-peak. Finally, the maximum value of the BCG wave between the K-negative-peak and the ECG T-peak was identified as the L-peak. Twenty-six features were obtained from the peaks of the BCGs. These features were the time intervals of each peak and the amplitude components, which are summarized in Table 1.

### 2.4 Personal identification using the BCG

In this study, the maximum number of people in one family is assumed to be five, which is twice as many as 2.44 people per household in Japan in 2018 [18]. Personal identification was performed in 21 (= 5C5) combinations that could be formed from five of seven subjects.

We performed personal identification using the BCGs during urination.

The accuracy of personal identification and equal error rate (EER) were calculated. The accuracy was calculated using the leave-one-out cross validation method. Figure 2 shows the algorithm for personal identification.

The BCG test data was segmented into heartbeats, and 26 features were extracted from each heartbeat. Then, the Mahalanobis distance ($MD_{ID}$) was calculated between the registered data and the test data as an evaluation function. First, we assumed that mother variance-covariance matrix was identical among all subject, and we calculated the average of the features and the variance-covariance matrix for each subject and $M_\sigma$ was obtained by Eq. (1).

$$M_\sigma = \frac{\sum_{ID}(n_{ID} - 1)\sigma_{ID}}{\sum_{ID}(n_{ID} - 1)}$$

where $\sigma_{ID}$ is the variance-covariance matrix for each subject, $n_{ID}$ is the number of the registered data for each subject, and $ID$ is the identification number of the subject. Next, feature $f$ was extracted from the test data, and the average feature $\overline{f}_{ID}$ was obtained from the registered data. We calculated the feature vector $F_{ID}$ using Eq. (2).

$$F_{ID} = (f_1 - \overline{f}_{ID1}, f_2 - \overline{f}_{ID2}, \ldots, f_{26} - \overline{f}_{ID26})$$

Finally, $MD_{ID}$ was calculated using Eq. (3).

$$MD_{ID} = \sqrt{F_{ID}M_\sigma^{-1}F_{ID}^T}$$

Then, the candidate result was decided by the nearest neighbor method using the $MD_{ID}$. These processes were performed for all of the heartbeats. Finally, the identification result was decided by majority vote using the candidate results. As reference result without the majority vote, the minimum average $MD_{ID}$ for each subject was used as the identification result.

The performance of the biometrics was analyzed by EER. EER is a biometric security system algorithm used to predetermine the threshold values for its false acceptance rate (FAR) and false rejection rate (FRR). The EER was calculated using FAR and FRR, assuming the probability of FAR and FRR being equal.

### Table 1 Features of the BCGs.

| Feature | Description |
|---------|-------------|
| JJ interval calculated from left sensor |
| HJ interval calculated from left sensor |
| JJ interval calculated from left sensor |
| JK interval calculated from left sensor |
| JJ interval normalized by JJ interval from left sensor |
| JK interval normalized by JJ interval from left sensor |
| JL interval normalized by JJ interval from left sensor |
| JJ interval calculated from right sensor |
| HJ interval calculated from right sensor |
| JJ interval calculated from right sensor |
| JK interval calculated from right sensor |
| JJ interval normalized by JJ interval from right sensor |
| JK interval normalized by JJ interval from right sensor |
| JL interval normalized by JJ interval from right sensor |

Difference between the peak of L wave obtained from both sensors

Difference between the peak of L wave obtained from both sensors

| Feature | Description |
|---------|-------------|
| I amplitude (Left sensor) / I amplitude (Right sensor) |
| J amplitude (Left sensor) / J amplitude (Right sensor) |
| K amplitude (Left sensor) / K amplitude (Right sensor) |
| L amplitude (Left sensor) / L amplitude (Right sensor) |
| I amplitude (Left sensor) / J amplitude (Left sensor) |
| K amplitude (Left sensor) / J amplitude (Left sensor) |
| L amplitude (Left sensor) / J amplitude (Left sensor) |
| I amplitude (Right sensor) / J amplitude (Right sensor) |
| K amplitude (Right sensor) / J amplitude (Right sensor) |
| L amplitude (Right sensor) / J amplitude (Right sensor) |
3. Results

3.1 Evaluation of BCG monitoring system
Figure 3 shows typical examples of a chest ECG (a) and the BCGs (b, c) recorded from the toilet seat during urination. Although a subject urinated, we had no record for the duration of the urination. Peaks H, I, J, K, and L of the BCGs were clearly obtained.

3.2 Personal identification results
Table 2 shows 21 personal identification results using the BCGs. The average accuracy was 92.2%. Maximum accuracy of 98% was obtained with the two combinations of ABCEF and ACEFG. Comparing the average accuracy for all subjects, subjects C and G had maximum accuracy of 100%, and subject D had minimum accuracy of 76%. Table 3 shows the EER results. The average EER was 34.1%.

3.3 Effect of majority vote
Figure 4 shows a comparison of the average accuracy of identification with and without the majority vote for each subject. The average accuracy of all subjects with the majority vote was 18.4% higher than that without the majority vote. In subject D, the worst accuracy was obtained both with and without the majority vote.

3.4 Voided volume
Figure 5 shows the distribution of voided volume for each subject. Each subject’s voided volume appears to be constant.

The relationship between the voided volume and average accuracy is shown in Fig. 6. Except for subject D, the average accuracy of identification without the majority vote appears to increase with an increase in voided volume. The regression line, excluding the data of subject D, is \( y = 0.042x + 62 \) (\( R^2 = 0.69 \)). On the other hand, with the majority vote, the average accuracy of identification seems to be flat with an increase in voided volume. The regression line, excluding the data of subject D, is \( y = 0.0078x + 92 \) (\( R^2 = 0.092 \)).

4. Discussion
In this study, we performed personal identification using the BCGs recorded from a toilet seat. Peaks H, I, J, K, and L of the BCGs were clearly obtained. However, peaks G, M, and N were unclear. Therefore, we discon-
continued using the features of peaks G, M, and N for personal identification. In this study, R wave of ECG was used to detect J wave of BCG. The self-warming toilet seat we used sometimes emits loud, intermittent electrical noises. If R wave cannot be detected clearly by the electrical noise, J wave cannot be detected. However, J-wave detection methods from BCG alone have been proposed using cross-correlation [19] and wavelet trans-

**Table 2** Identification results.

| Subject | ABCDE | ABCDF | ABCDG | ABCEF | ABCEG | ABCFG | ABDEF | ABDEG | ABDFG | ABEFG | ACDEF |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| A       | 90    | 90    | 90    | 80    | 100   | 90    | 80    | 90    | 100   | 80    | 100   |
| B       | 100   | 90    | 100   | 90    | 100   | 90    | 90    | 100   | 100   | 90    | —     |
| C       | 100   | 100   | 100   | 100   | 100   | 100   | 100   | 100   | 100   | 100   | 100   |
| D       | 70    | 80    | 80    | —     | —     | 80    | 70    | 80    | —     | 70    | —     |
| E       | 80    | —     | —     | 90    | 90    | —     | 90    | 90    | —     | 90    | 80    |
| F       | —     | 100   | —     | 100   | —     | 100   | 100   | —     | 100   | 90    | 100   |
| G       | —     | —     | 100   | —     | 100   | 100   | 100   | —     | 100   | 100   | 100   |
| Average | 88    | 92    | 94    | 92    | 98    | 96    | 88    | 90    | 96    | 90    | 90    |

**Table 3** EER results.

| Combination of subjects | EER [%] |
|-------------------------|---------|
| ABCDE                  | 33.3    |
| ABCDF                  | 37.0    |
| ABCDG                  | 30.2    |
| ABCEF                  | 35.9    |
| ABCEG                  | 27.7    |
| ABCFG                  | 31.7    |
| ABDEF                  | 36.2    |
| ABDEG                  | 28.5    |
| ABDFG                  | 32.0    |
| ABEFG                  | 30.0    |
| ACDEF                  | 41.9    |
| ACDEG                  | 38.0    |
| ACDFG                  | 37.9    |
| ACEFG                  | 36.2    |
| ADEFG                  | 37.5    |
| BCDEF                  | 38.2    |
| BCDEG                  | 30.7    |
| BCDFG                  | 33.8    |
| BCEFG                  | 30.8    |
| BDEFG                  | 31.6    |
| CDEFG                  | 37.2    |
| Average                | 34.1    |

Fig. 4 Comparison of accuracy of identification with and without the majority vote.
By introducing these methods in this study, J wave can be detected without using the ECG. The accuracy without the majority vote was the worst in subject D, because similar features with other subjects were obtained. Although the accuracy was worst in this subject, the majority vote was effective for personal identification. Even with similar features, the accuracy with the majority vote was better than that without the majority vote in all subjects (Fig. 4). In Figure 5, the voided volume for each subject is approximately constant. We assume that all subjects in this study have a constant normal urine flow rate. A large voided volume requires a long sitting time because of the constant urine flow rate. Sitting for a long time yields many heartbeats that provide much data of the features for personal identification. It is considered that the average accuracy of identification without the majority vote, with the exception of subject D, increases with increasing voided volume (see open squares in Fig. 6). Therefore, a large voided volume may provide more data of the features for identification.

Consider a case in which nine heartbeats are obtained from a person during urination. Even if the features of four heartbeats lead to wrong identification as another person, if the features of the remaining five heartbeats lead to correct identification as the person, the correct answer can be obtained using the majority vote. Thus, the use of majority vote contributes to the improvement of accuracy, but it increases the EER. A performance evaluation of seven biometric systems—including face, fingerprint–chip, fingerprint–optical, hand, iris, vein, and voice—was reported [21]. In the report, all biometric EERs were less than 10%. In the present study, the average EER was 34.1%, which was higher than those of other biometrics. The EER indicates the probability of obtaining a false identification result. We obtained voided volume [2] and toilet seat ECGs [11, 12] during urination. The voided volume was approximately constant for each subject (Fig. 5). Therefore, it may be useful to introduce features such as voided volume and toilet seat ECGs, in addition to BCGs, to improve accuracy and reduce the EER.

In this study, personal identification was performed using the algorithm selected from five registered subjects. This algorithm does not support non-registered persons. Therefore, if a non-registered person uses the toilet, a misidentification result will be obtained. In the next step, improvement must be made in the candidate determination procedure in Fig. 2 to add an algorithm to identify non-registered persons as guests. The improved algorithm that identifies individuals from five registered subjects and guests will introduce an MDID threshold. In the personal identification test, a candidate is decided to be a guest if the calculated MDID is larger than the MDID threshold for each heartbeat. Finally, the identification result will be decided by majority vote using the results of the candidates including a guest. By improving the algorithm in this way, it is expected to prevent misidentification result when non-registered persons use the toilet.

The BCG waveform may change according to sitting posture on the toilet seat and health condition. Changes in the BCG waveform worsen personal identification result. However, if the registration data can be updated by increasing the number of registration data for each toilet use, the candidate decisions will be robust against small changes in the BCG waveform due to changes in sitting position and changes in health condition. As a result, good personal identification results may be obtained by updating the registered data for each toilet use. Moreover, since the voided volume for each subject is approximately constant, introducing voided volume as a feature may improve personal identification results.

To prevent infection, touching the sensors should be avoided when using biometrics. To protect personal privacy, use of visual cameras should also be avoided, espe-
cially in toilets and bathrooms. We achieved personal identification using the BCGs recorded from a toilet seat. This method is a good candidate because it prevents infection and protects personal privacy. Moreover, we were able to measure the BCGs using vibration sensors installed beneath the toilet seat, and peaks H, I, J, K, and L of the BCGs were clearly obtained. As ECG can be monitored from the toilet seat [11], it may be possible to estimate blood pressure using both BCG and ECG.

5. Conclusion

In this study, we achieved personal identification using BCG with the aim to establish a biometric identification method for the healthcare system by collecting physiological data in the toilet. We developed a BCG monitoring system in which two vibration sensors were installed beneath the toilet seat to measure BCG while a participant sit on the toilet seat. The BCGs during urination were recorded, and peaks H, I, J, K, and L were clearly obtained. Personal identification was performed using the features of the BCGs. The results of personal identification showed average accuracy of 92.2% and average EER of 34.1%. Although EER was not sufficiently low, average accuracy suggested that the proposed method using a toilet seat may provide adequate biometrics for application in the healthcare system.

Conflict of Interest

We have no conflicts of interest or relationship with any companies or commercial organizations, based on the definition of the Japanese Society for Medical and Biological Engineering.

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