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EFFECTS OF MEASUREMENT POSITIONS AND EMOTIONAL CHANGES ON ECG INDICES: A PRELIMINARY STUDY

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Abstract. *Recently, biometric technology has been actively used in various fields, both in academia and industry. This study was conducted as a preliminary study to determine the possibility of stable analysis based on electrocardiogram (ECG) measurement location and emotional changes. We started by arranging portable ECG measurement devices and developing signal processing algorithms. Experiments were conducted on four participants (mean age: 21.8 years). ECG signals were measured at two positions (at the wrists and fingertips) while the participants viewed four categories of photographs (positive, negative, natural environment, and fear related) exposed by balancing the order. The collected ECG signals were refined to a total of 29 indicators after signal processing. As a result of the analysis, the ECG was stably collected, regardless of the change in emotions and measurement position. However, there were individual differences between participants. The results of this study are expected to be useful reference material for ECG authentication research.*

Keywords: Biometrics, Electrocardiogram (ECG), Sensors, Personal authentication, Emotion

1. **Introduction.** Biometrics refers to a class of technology that involves the measurement and analysis of body metrics, related to certain physical human characteristics (e.g., fingerprints, faces, iris), as well as behavioral characteristics (e.g., voice signature, gait) [1]. In computer science, biometric information can be utilized in biometric identity authentication. Recently, biometrics has been widely used in a variety of fields such as immigration screening, e-commerce, telecommunications, and medical services [2]. According to Acuity Market Intelligence, global mobile biometric market revenues are increasing every year, and in 2022 it is expected to reach 50.6 billion dollars [3]. Recently, ECG biometrics has been applied in automobiles as well as smart mobile devices (SMDs) [4]. Biometrics connected to a vehicle does not only provide convenience in terms of personal authentication, but can also detect a driver's health and wellbeing.

Ergonomic research based on ECGs has mainly been conducted to understand human conditions and context [5-9]. In particular, there has been ongoing research to interpret the driver's mental workload [5-7,9]. These studies include a study that analyzed the

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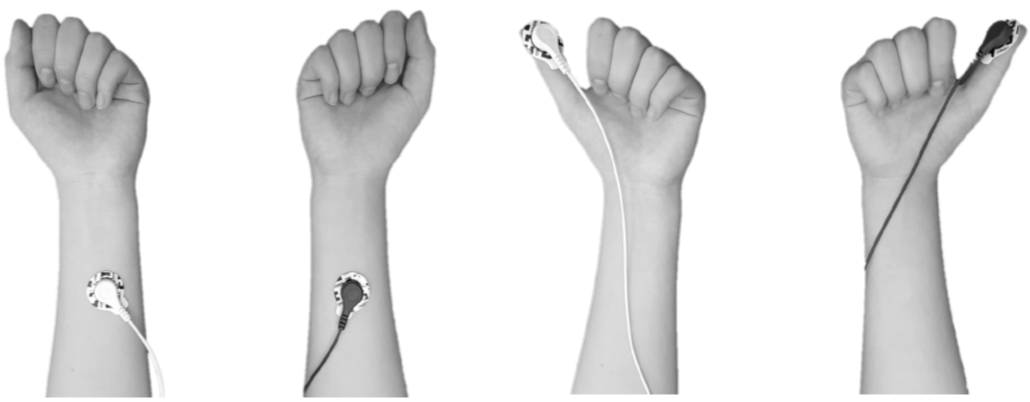
changes in heart rate variability, and T-wave application of the ECG to check the mental workload of a train driver [5]; a study that analyzed the ECG and eye movement of a bus driver whilst driving [6]; a study to check the mental workload by measuring the participant's ECG during driving in the lane change task (LCT) [9]; and a study to measure the ECG and eye tracking during a flight task to improve the pilot's mental workload [7].

Furthermore, studies on ECG-based personal authentication systems have also been actively pursued [10-16]. [12] collected ECG signals from two participants' fingers using an ECG sensor pad. [13] conducted a study to measure and analyze ECG data on both wrists (using MP150), while participants performed various tasks including resting, exercise, listening to music, and watching videos. [14] conducted a study to extract personal data from stable ECGs and to analyze the data in order to improve personal authentication performance.

Previous studies have focused on identifying human characteristics, or improving the performance of algorithms in specific areas, using high-performance equipment. In contrast, this study tries to determine whether a person's mental characteristics, or authentication, is possible using portable equipment. For reference, the driving situation is taken into account in a long-term perspective. As a preliminary experiment, this study was intended to identify differences in ECG indices, depending on the measurement position and emotional changes.

2. **Methods.** There were four participants and the average age was 21.8 years old (± 0.4). The participants were all healthy college students with no heart problems. All participants agreed to the collection of their personal information, and received a small payment for participating in the experiment.

This experiment used ECG sensors that were developed using an Arduino to measure the ECG of participants. The sampling rate of the ECG sensor was 1138 Hz. Sensors were worn on both wrists or both fingertips of the participants. Figure 1 shows the sensor's attachment position.



(a) Wrists (b) Fingertips

FIGURE 1. Position of sensor attachment: (a) wrists, (b) fingertips

The participants were seated in a comfortable chair and then viewed the photographs on a desktop computer. The photographs were related to positive, negative, natural environment, and fear representations. The photographs were presented to induce related emotions. The images were searched for by using related keywords on a portal site, such as Google, and only images without copyright protection were selected. The participants were exposed to 10 photographs of each category for 10 seconds per photograph. Figure 2 illustrates the four categories.

(a) Positive

(b) Negative

(c) Natural environment

(d) Fear

FIGURE 2. Photograph of four categories: (a) positive, (b) negative, (c) natural environment, (d) fear

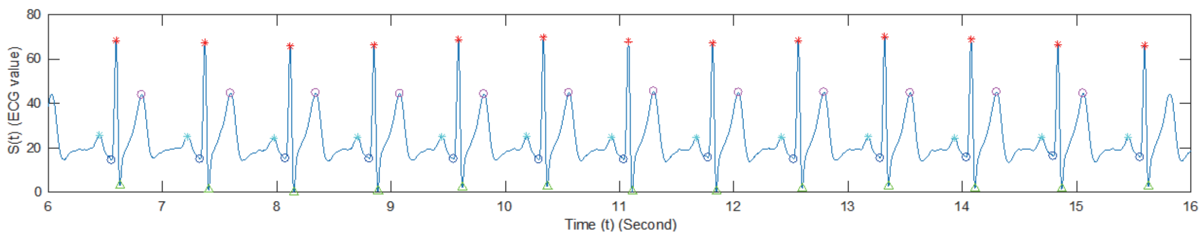


FIGURE 3. (color online) Extracted PQRST complexes in ECG waveform of subject 1 (light blue *: P, blue ∘: Q, red *: R, green △: S and pink ∘: T)

The experiment was designed for participants to wear the ECG sensors, have their ECG measured for 1 minute (when stabilized), and then for additional experimental work to be performed. The procedure was repeated after changing the attachment position of the ECG sensor. The order of photographs' emotional type, and sensor attachment position, was different for each participant in order to minimize the effects of order.

We developed a feature extraction algorithm to extract PQRST peaks from the four participants using certain conditions of the amplitudes and intervals. Figure 3 illustrates the ECG signal and extracted PQRST features from subject 1. A total of 29 ECG indicators were derived and analyzed to evenly represent the PQRST waveforms. After deriving the indicators, MANOVA was used to determine whether emotional types (i.e., positive, negative, natural environment, fear) and sensor attachment positions (i.e., both wrists and both fingertips) had significant effects on the indicators. In the analysis process, one of the participants confirmed that the PQRST waveform was not collected correctly, and was consequently excluded from the analysis.

3. **Results.** A total of 29 values, including time and frequency domains, were derived as ECG indices. A summary of the indicators is shown in Table 1. In order to develop algorithms by selecting them from further analyses, some metrics separately extracted global data, and time window data, over 10 seconds. We extracted PQRST peaks from global data and time window data using a developed feature extraction algorithm. ECG indicators derived from the PQRST waveforms of global data and time window data are as follows. Mean RR_G, SDNN_G, Mean ST_G, SDST_G, Mean PR_G, SDPR_G are indicators related to global data and Mean RR_W, SDNN_W, Mean ST_W, SDST_W, Mean PR_W, SDPR_W are indicators related to window data. rrHRV is the HRV calculated based on the relative RR intervals. Median, IQR, Shift x, and Shift y are indicators representing rrHRV.

Table 1. ECG indicators

ECG feature	Description
Median	Median of rrHRV
HF	Spectral power of the RR time series in the band [0.15 Hz-0.4 Hz], high frequency power
IQR	Inter-quartile range of rrHRV
LF/HF	Ratio between LF and HF
Shift x	X-axis of HRV center point matrix
Mean RR_G	Average RR intervals from global data
Shift y	Y-axis of HRV center point matrix
SDNN_G	Standard deviation of the RR intervals from global data
Mean RR	Average RR intervals
Mean ST_G	Average of ST segment from global data
Mean HR	Average heart rates
SDST_G	Standard deviation of ST segment from global data
SDNN	Standard deviation of the RR intervals
Mean PR_G	Average of PR segment from global data
RMSSD	Root mean square of the difference of all subsequent RR intervals
SDPR_G	Standard deviation of PR segment from global data
pNN50	Percentage of RR intervals in which the change of successive NN exceeds 50 ms
Mean RR_W	Average RR intervals from window data
TRI	Triangular index from the RR interval histogram
SDNN_W	Standard deviation of the RR intervals from window data
TINN	Base of the triangle used to approximate the histogram of the RR time series
Mean ST_W	Average of ST segment from window data
SD1 or SD2	Standard deviations of Poincare plot
SDST_W	Standard deviation of ST segment from window data
SD1/SD2	Ratio between S1 and S2
Mean PR_W	Average of PR segment from window data
LF	Spectral power of the RR time series in the band [0.04 Hz-0.15 Hz], low frequency power
SDPR_W	Standard deviation of PR segment from window data

The MANOVA results showed that the type of emotions and the sensor attachment position, did not have a statistically significant effect on the ECG index (at a significance level of 0.05). There is no interaction effect between emotional type and sensor attachment position. Additionally, we found that there was a statistically significant difference in some of the indicators between participants (Table 2). There was a statistically significant difference between the participants in their Median, Mean RR, Mean HR, pNN50, SD1/SD2, LF, HF, LF/HF, Mean RR_G, Mean PR_G, Mean RR_W, Mean ST_W, and SDST_W ECG indicators (Table 3).

Table 2. Results of multivariate test of emotion type, sensor position, participant

	Emotion type		Sensor position		Participant	
	F	p	F	p	F	p
Pillai's Trace	0.784	0.712	0.592	0.759	1.665	0.335
Wilks's Lambda	0.523	0.867	0.592	0.759	3.694	0.235
Hotelling's Trace	N/A	N/A	0.592	0.759	0.000	N/A
Roy's Largest Root	9.039	0.026	0.592	0.759	61.485	0.016

Table 3. Results of tests of between-subjects effects of participants

Indices	F	p	Indices	F	p
Median	6.984	0.009	LF	25.862	0.000
IQR	1.608	0.238	HF	25.862	0.000
Shift x	0.659	0.534	LF_HF_ratio	29.445	0.000
Shift y	0.664	0.532	Mean RR_G	4.970	0.025
Mean RR	12.022	0.001	SDNN_G	1.384	0.285
Mean HR	11.127	0.002	Mean ST_G	2.187	0.152
SDNN	0.401	0.678	SDST_G	0.997	0.396
RMSSD	3.735	0.052	Mean PR_G	14.258	0.001
pNN50	5.863	0.015	SDPR_G	1.476	0.264
TRI	0.008	0.992	Mean RR_W	14.081	0.001
TINN	0.352	0.710	SDNN_W	2.814	0.096
SD1	3.739	0.052	Mean ST_W	28.996	0.000
SD2	0.047	0.955	SDST_W	9.771	0.003
SD1_SD2_ratio	5.232	0.022	Mean PR_W	1.253	0.318
			SDPR_W	0.946	0.414

4. **Discussion.** Here, we measured ECGs of participants while they viewed four categories of photographs (positive, negative, natural environment, and fear related) that caused emotions in two sensor attachment locations (both wrists and both fingertips). The results of the MANOVA show that the emotion type and sensor position do not have a statistically significant effect on ECG readings, and that there is no significant difference in the interaction effect between the two. This showed that there was no problem in the sensor and measuring components used in this experiment. However, there were statistically significant differences among participants with regard to some indicators. This confirms that both measurement locations (wrists and fingertips) are capable of stable data collection and that there are individual differences. This is consistent with the findings of previous studies. In previous studies [12-14], the studies on ECG-based personal authentication systems have been conducted when collecting ECG signals at positions including wrists and fingertips. As a result, stable personal authentication at those positions has been confirmed.

Generally, ECG signals are first analyzed through feature extraction and classification [17]. [12] used R-peak, heartbeat, mean wave, and median wave as ECG indices for analysis. [11,15,16] extracted the QRS complex and confirmed the performance of individual authentication. [14] studied the identification performance using a heartbeat image. Here, a total of 29 indicators were extracted from ECG signals to analyze PQRST waveforms in a variety of ways. Compared to previous studies, this can be viewed as varied. Therefore, this study analyzed the ECG signals using various indicators compared with previous studies and confirmed the effects of sensor position and emotion type. There are some limitations to this study. First, due to the limited number of participants in the experiment, there is a lack of research effectiveness for full-scale algorithm development or individual authentication. In future, a larger number of participants will be mobilized to participate in ECG experiments and analyses across various situations. The fingertips are considered as wearing parts referring to the results of this study. Second, it is different from some previous studies in that there is no indicator difference based on individual psychological difference [18]. The reason for this can be analyzed in several ways, such as that the photographs used in this study were not intense enough to cause emotion, and/or that, as mentioned earlier, the limited number of participants in the experiment did not represent many cases in practice. This study excluded photographs that could cause serious fear, in order not to provoke participants too much.

On the other hand, this study was conducted considering the application of personal authentication technology in automobile fields. The results are similar to previous studies that stable ECG signal is measured at the wrists and fingertips. However, this study confirmed the changes in measurement positions did not affect the ECG indices. The results seemed that stable personal authentication is possible at the fingertips as well as the wrists. In addition, the effects of changes in emotions on ECG indices were confirmed. In particular, in this study, the various indicators were used to determine the effects of changes in measurement positions and emotions on ECG indicators.

5. **Conclusions.** Here, the effects of measurement positions and emotions on ECG indicators were identified. The participant measured the ECG signal according to the position of the sensor during the process of viewing the photographs that cause emotion. The collected ECG signals were refined into 29 different indicators. Emotion type and sensor position did not statistically affect the ECGs. There was a statistically significant difference in the ECGs of the participants. This study was conducted as a preliminary study for personal authentication based on the ECG of a motor vehicle driver. In future, the portable sensor will be used to collect electrocardiographic information in various situations, including the driving situation, and in conducting psychological and situational analyses.

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