Laser-Based Noncontact Blood Pressure Estimation Using Human Body Displacement Waveforms

Yuji Oyamada#, Takehito Koshisaka#, Grant Stankaitis$, Shekh M. M. Islam*, Victor M. Lubecke$, Olga Borić-Lubecke$, Takuya Sakamoto#1
#Graduate School of Engineering, Kyoto University, Japan
$Department of Electrical Engineering, University of Hawaii at Manoa, USA
*Department of Electrical and Electronic Engineering, University of Dhaka, Bangladesh
1sakamoto.takuya.8n@kyoto-u.ac.jp

Abstract — **Measurement of the body's displacement at multiple positions allows heart pulse wave propagation to be observed; this is an important step toward noncontact blood pressure measurement. This study investigates the feasibility of performing blood pressure measurements using skin displacement waveforms measured at two positions on a human body. To evaluate the accuracy of the proposed approach, this study uses a pair of laser displacement sensors to enable precise pulse transit time measurement. By comparing the displacement waveforms from the two sensors, the relationship between pulse transit time and blood pressure was evaluated. It is demonstrated experimentally that the blood pressure can be estimated with accuracy of 5.1 mmHg, which is equivalent to the error of an ordinary cuff-type blood pressure monitor.**

Keywords — **biomedical engineering, displacement measurement, physiology.**

I. Introduction

Cardiovascular disease is the leading cause of death globally, with estimated 17.9 million lives lost annually [1]. Because the risk of cardiovascular disease increases with high blood pressure (BP) [2], it is important to measure patient BP on a long-term basis. Recently, in addition to the conventional measurement method for BP estimation using a contact-type cuff [3], [4], new approaches to BP measurement without a cuff have also been investigated.

One such method is based on the use of photoplethysmography (PPG) sensors, and PPG-based methods have been investigated in the following ways: BP estimation by obtaining the pulse transit time (PTT) using an electrocardiogram (ECG) sensor and a PPG sensor [5], using PPG sensor waveforms and machine learning [6], and using PPG signals alone [7]. In addition, Buxi et al. [8] proposed a method to obtain the PTT and estimate the BP using continuous wave radar, an ECG sensor, and the patient's electrical bioimpedance.

However, these methods are not suitable for long-term BP monitoring because of the discomfort caused by the contact between the patient's body and the measurement device. Zhao et al. [9] used a single radar system to obtain the PTT between the carotid and femoral arteries and thus estimate the BP. This study used the features found in [10], which means that the BP cannot be obtained if these features are not observed in the displacement waveform, as is often the case. Jung et al. [11] also studied a method for BP estimation using a single 300 GHz continuous wave radar system and machine learning. Although their study used the dataset for machine learning from [12], it is uncertain if the BP can be estimated correctly using this method because their training data were not obtained using radar.

In this study, the feasibility of BP measurement using the body displacements caused by pulse waves at multiple positions on a human body is investigated. It is assumed that this approach is applied to the radar-based measurement method reported in [13], in which pulse waveforms were measured at two positions simultaneously using a 79-GHz radar array and the high accuracy of the method was verified via comparison with data from laser-based displacement sensors. As a preliminary study, this study uses a pair of laser displacement sensors and focuses on the feasibility of measuring both the PTT and the BP using pulse waveforms at two positions on a human body.

Table 1. Specifications of the laser displacement sensor.

Measurement displacement	150 ± 40 mm
Spot size (diameter)	120 μm
Resolution	0.2 μm
Sampling period	100 μ s
Wavelength	655 nm

II. Body Displacement and BP Measurement

In this study, to investigate the BP estimation accuracy, pulse wave measurements are performed using laser displacement sensors because laser displacement sensors measure the skin displacement accurately, although they do require the target person's body to be exposed by partially removing their clothing, as shown in Fig. 1. The specifications of the laser displacement sensors CDX-150 (Optex FA Co., Ltd., Kyoto, Japan) used in this study are shown in Table 1. The sensors are categorized as a diffuse reflection model. A pair of laser sensors was used to measure the displacements at two positions (the patient's chest and abdomen), as shown in Fig. 1. Specifically, laser displacement sensors with a wavelength of 655 nm, a spot size diameter of 120 μm, a sampling frequency of 10 kHz, and reproducibility of 0.2 μm

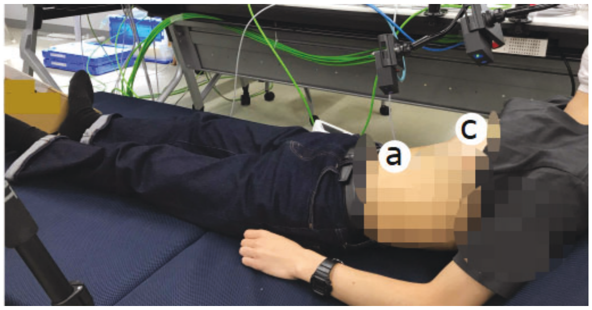

Fig. 1. Photograph of the measurement setting with a participant and laser displacement sensors.

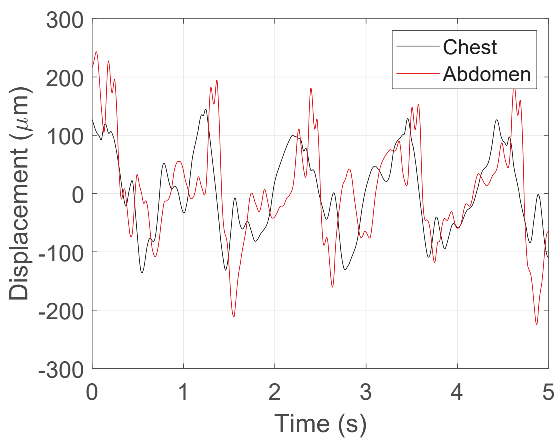

Fig. 2. Body displacement waveforms obtained from the laser displacement sensors.

were used. An example of the body displacements measured using the laser displacement sensors is shown in Fig. 2. The black and red lines represent the displacement waveforms $d_{\mathrm{c}}(t)$ and $d_{\mathrm{a}}(t)$, which correspond to the measurements of the chest and abdomen, respectively.

Four healthy male adults in their twenties participated in this study as volunteers. The BPs of each participant were measured using a contact-type BP monitor, the HEM-7133 sphygmomanometer (Omron Corporation, Kyoto, Japan), for use as reference data. In this study, the measurements were performed approximately fifty times every 20 minutes for each participant using two laser displacement sensors and the BP monitor.

III. BP Estimation using Body Displacements at Two Positions

In this section, the following relationship between the pulse waveforms and the BP is investigated. The N-dimensional vectors denoted by

$$\begin{aligned} \boldsymbol{d}_{\mathrm{c}}(t) &= [d_{\mathrm{c}}(t), d_{\mathrm{c}}(t+\Delta t), \cdots, d_{\mathrm{c}}(t+(N-1)\Delta t)]^{\mathrm{T}}, \\ \boldsymbol{d}_{\mathrm{a}}(t) &= [d_{\mathrm{a}}(t), d_{\mathrm{a}}(t+\Delta t), \cdots, d_{\mathrm{a}}(t+(N-1)\Delta t)]^{\mathrm{T}} \end{aligned} \tag{1}$$

are defined, where the superscripted T denotes a matrix transpose, and Δt is the sampling interval. The

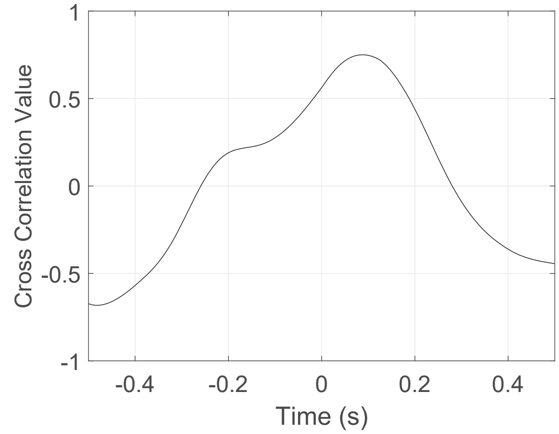

Fig. 3. Example of $\rho(\tau)$ for the displacement waveforms $d_{\mathrm{c}}(t)$ and $d_{\mathrm{a}}(t)$.

cross-correlation function $\rho(\tau)$ between the displacement waveforms for the chest and the abdomen is given by

$$\rho(\tau) = \frac{\boldsymbol{d}_{\mathrm{c}}^{\mathrm{T}}(t_0)\boldsymbol{d}_{\mathrm{a}}(t_0+\tau)}{|\boldsymbol{d}_{\mathrm{c}}(t_0)||\boldsymbol{d}_{\mathrm{a}}(t_0+\tau)|}, \tag{2}$$

where t_0 is the start time for the displacement waveform of the chest, and τ is the time lag. Note that $\rho(\tau)$ is normalized and the condition $|\rho(\tau)| \leq 1$ is satisfied. Using $\rho(\tau)$, the PTT (τ_{PTT}) is estimated as $\tau_{\mathrm{PTT}} = \arg\max_\tau |\rho(\tau)|$. Using waveforms in Fig. 2, $\rho(\tau)$ was calculated as shown in Fig. 3. We perform a linear regression between the PTT (τ_{PTT}) and the BP (p) to estimate the BP. We performed a total of $N = 50$ measurements of pairs of PTT and BP values and obtained $(\tau_1, p_1), (\tau_2, p_2), \cdots, (\tau_N, p_N)$. We then normalized the PTT and BP data as $\tau_i' = (\tau_i - \bar{\tau})/\sigma_\tau$ and $p_i' = (p_i - \bar{p})/\sigma_p$ $(i = 1, 2, \cdots, N)$, respectively, where $\bar{\tau}$ and $\bar{p}$ are the means of the PTT and BP data, respectively, and σ_τ and σ_p are the standard deviations of the PTT and BP data, respectively.

We performed at least-squares minimization to determine the linear regression $p_i' = \alpha\tau_i'$, as shown in Fig. 4, where the systolic blood pressure (SBP) is shown as an example. Here, a k-fold cross validation was used to investigate the feasibility of the noncontact BP measurements, where a value of $k = 5$ was selected. In a k-fold cross-validation, data samples are divided into k groups, of which $k - 1$ groups are used for training and the remaining one is used for testing. In Fig. 4, the black circles represent the training data and the red line is the orthogonal regression line. The blue line represents the 95% confidence ellipse for the data plots.

Table 2 shows the results from the 5-fold cross-validation, including the root mean square error (RMSE) for the BP estimation of one of the participants. The contribution ratio values of the SBP, the mean BP (MBP), and the diastolic BP (DBP) were 0.63, 0.68, and 0.67, respectively, indicating a relationship between the PTT and the BP. Note that the contribution ratio is defined as $\Lambda_1/(\Lambda_1+\Lambda_2)$ using eigenvalues Λ_1 and Λ_2 of the correlation matrix, where $\Lambda_1 \geq \Lambda_2$ holds. The maximum RMSE was approximately 6 mmHg, which

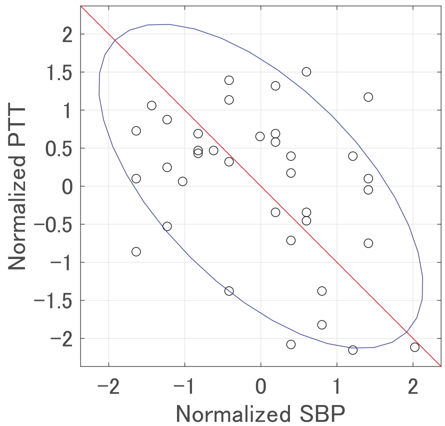

Fig. 4. Relationship between SBP and PTT obtained from the measurements.

Table 2. Performance evaluation of BP estimation from body displacements.

		training data	test data
SBP	Data Mean (mmHg)	110.69	110.51
	RMSE (mmHg)	5.96	6.05
	Error Mean (mmHg)	0.00	0.07
	Contribution Rate	0.63	-
MBP	Data Mean (mmHg)	87.63	87.39
	RMSE (mmHg)	4.30	4.49
	Error Mean (mmHg)	0.00	−0.04
	Contribution Rate	0.68	-
DBP	Data Mean (mmHg)	76.10	75.82
	RMSE (mmHg)	4.64	4.80
	Error Mean (mmHg)	0.00	−0.07
	Contribution Rate	0.67	-

is consistent with the results of Ringrose et al. [14], which showed that 69% of home BP monitors have errors equal to or greater than 5 mmHg. In this study, the SBP, and DBP ranged from 103–121 mmHg, and 68–88 mmHg, respectively.

IV. Conclusion

In this study, to investigate the accuracy limit of noncontact BP measurement using the PTT data calculated from body displacement waveforms measured at multiple positions on the human body, we introduced a precision measurement method using laser displacement sensors. The resulting root mean square error in measuring the BP was almost in the same order as that of common home BP monitoring device, indicating the possibility of practical application of the noncontact BP measurement method using the body displacements at multiple positions on the human body. Future work may include using displacement measurements obtained by other methods, including radar.

Acknowledgment

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Ethics Declarations

This study was approved by the Ethics Committee of the Graduate School of Engineering, Kyoto University (permit no. 201916). Informed consent was obtained from all participants in the study.

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