Efficient Blood Pressure Estimation Using Seismocardiogram and Electrocadiogram

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Abstract*— Our research team has developed a device for monitoring cardiac signals in the carotid artery. This device enables the simultaneous measurement of various cardiovascular signals, including Photoplethysmogram (PPG), Phonocardiogram (PCG), Electrocardiogram (ECG), and Seismocardiogram (SCG). This study estimates blood pressure based on cardiac signals measured in the carotid artery and utilizes deep learning to minimize the sensors requirements for the estimation. Our approach focused on utilizing Seismocardiogram (SCG) and Electrocardiogram (ECG) signals for blood pressure estimation. By strategically leveraging the complementary nature of these signals, we aim to streamline the estimation process, reducing the need for extensive sensor fusion. To this end, our teams adapted the Long Short-Term Memory (LSTM) architecturefor for minimalist sensor fusion model. This model is trained on the Chemical Effects in Biological Systems (CEBS) database to extract features from sensor data. Additionally, the model demonstrates the ability to restore ECG data from SCG inputs, highlighting the feasibility of predicting ECG signals using only SCG sensors. This research contributes a resource-efficient paradigm to blood pressure estimation, prioritizing simplicity and minimizing sensor requirements. By emphasizing the independent utilization of SCG sensors in blood pressure estimation, our approach provides a practical solution for developing wearable health monitoring devices with reduced complexity and enhanced efficiency.

Keywords—Wearable Health Monitoring, Blood Pressure Estimation, Seismocardiogram

I. Introduction

Various devices for health monitoring have been extensively developed. However, leveraging the data from these diverse devices for AI applications often requires significant preprocessing due to mismatched timelines. The quality of data significantly impacts AI performance, necessitating high-quality training data for optimal results [1]. Recent trends focus on maximizing AI performance while providing users with optimal resources, leading to the emergence of devices designed to estimate blood pressure using various data sources, even with minimal hardware. In response to these trends, this paper aims to demonstrate the feasibility of blood pressure estimation, using effective training data from a single device and minimal hardware resources.

II. Method

A. Development of a Multi-Biosignal measurement Platform

A system was developed with nRF52840 (Nordic Semiconductor, Norway) as the core for measuring PPG, ECG, SCG, and PCG signals and establishing Bluetooth Low Energy (BLE) communication. Initially, PPG signals are acquired using the I2C protocol, while ECG, SCG, and PCG signals are obtained through a 12-bit ADC. For PPG and ECG measurements, MAX30102 (Analog Devices, USA) and AD8232 (Analog Devices, USA) are utilized, respectively. PCG and SCG are measured by configuring a circuit to receive PCG, followed by measuring SCG from the node before passing through a High-pass filter (HPF). Finally, the collected biosignal data is transmitted to peripheral devices through BLE communication. The research initiates with the measurement of four heart-related signals (PPG, ECG, SCG, PCG) and the implementation of a BLE communication system with a PC [2]. A blood pressure estimation algorithm based on the time interval between the ECG R-peak and SCG AC-peak is implemented. The device is miniaturized through PCB design, with multiple layers hosting different components, and the entire system is encapsulated using a custom silicone mold. The sensor measurement locations are illustrated in Fig. 2.

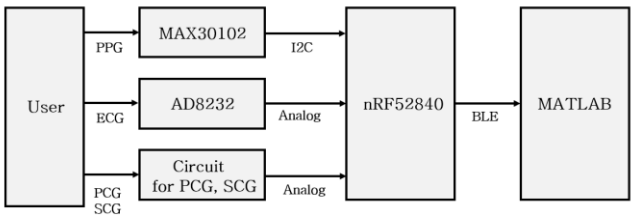

Fig. 1. System Schematic.

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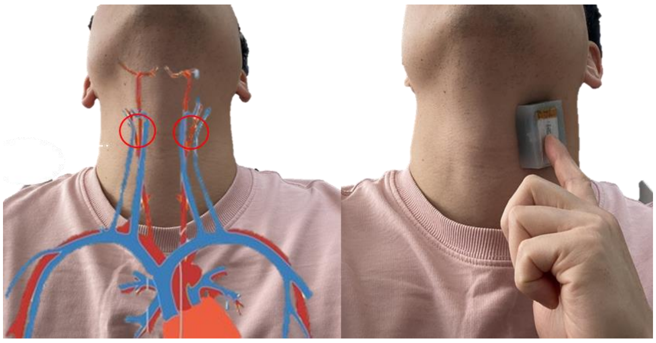


Fig. 2. The sensor measurement locations on the carotid artery section

B. Signal Processing & Blood Pressure Estimation Algorithm

The biosignals sent via BLE communication from the nRF52840 are processed in MATLAB. Each biosignal undergoes frequency-domain filtering, with PPG retaining the 0.5-8Hz range and ECG eliminating noise below 0.5Hz using MATLAB's built-in frequency-domain filtering functions. SCG and PCG assist in additional noise reduction. Peak detection is performed on the SCG signal within 360ms after the ECG R-peak to identify the S1 phase. This allows the detection of the MO-peak while considering an AC-peak occurring 18ms before the MO-peak [3][4][5]. Blood pressure is estimated using the RAC method in MATLAB, representing the time difference between the ECG R-peak and SCG AC peak. The ejection time is derived from RAC time, and blood pressure is estimated [5]. Correction algorithms considering the user's height, weight, and age are incorporated. The algorithm follows the equations below.

$$BSA = 0.07184 * Weight^{0.425} * Height^{0.725} \tag{1}$$

$$SV(mL) = -6.6 + 0.25 * (ET - 35) - 0.62 * HR + 40.4 * BSA - 0.51 * Ag \tag{2}$$

$$P_P = HR * SV * Z \frac{SV}{(0.013*Weight - 0.007*Age - 0.004*HR) + 1.307} \tag{3}$$

$$P_m = Q * R \tag{4}$$

$$P_S = P_m + \frac{2}{3} P_p \tag{5}$$

$$P_d = P_m - \frac{1}{3} P_p \tag{6}$$

SV: Stroke Volume

P_m: Mean Arterial pressure

P_S: Systolic Pressure

P_p: Pulse Pressure

HR: Heart Rate

ET: Ejection Time

BSA: Body Surface Area

Q: Cardiac Output

Z: Impedance to blood flow

R: Resistance to blood flow

C. Sequential data Prediction model

In the context of time series data prediction, an LSTM network was employed to forecast ECG data utilizing SCG data, taking into consideration long-term dependencies. The dataset used in this study was obtained from CEBS data. A total of 19 subjects were included in the analysis, with both ECG and SCG measurements collected simultaneously. The dataset had a high sampling frequency, resulting in a substantial volume of data. Consequently, the data underwent downsampling, and the downsampled signals were segmented into approximately two cycles of cardiac signals for training purposes [6].

III. Result

A. Multi-biosignal Platform Result

To attach the device to the carotid artery, miniaturization is essential. Three 30 mm by 40 mm PCBs, each with connectors, are designed and folded in a 3-layer fashion. The top PCB includes three ECG electrodes, sensors for PPG, and a microphone for PCG and SCG measurements. The middle PCB contains ECG sensors and PCG/ SCG sensors, while the bottommost PCB contains the BLE module. Firstly, the schematic for the first board includes three ECG electrodes, a microphone, and MAX30102 for PPG. Exclusively for the MAX30102 chip, separate regulation is required to supply the necessary 1.8 V DC voltage for LED operation, distinct from other components. The signal processing units for SCG and PCG, along with the ECG electrodes and AD8232, are connected between boards using an FFC cable. The connected configuration is illustrated in Fig. 3.

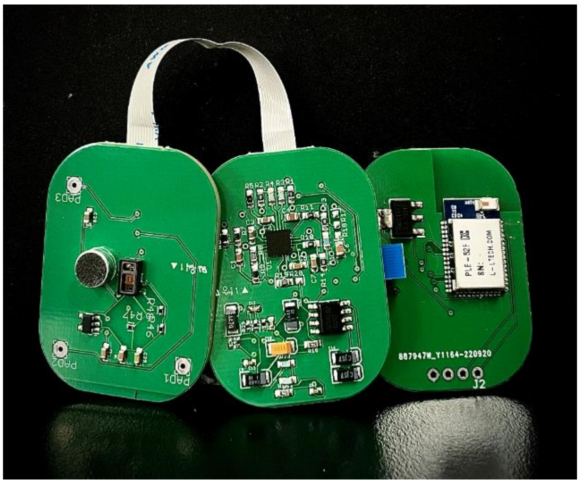
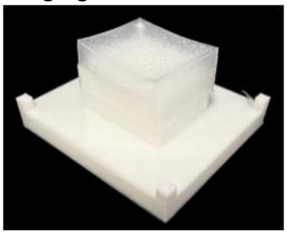


Fig. 3. Designed PCB

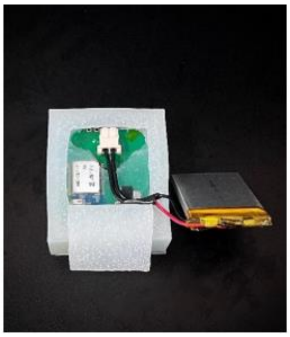
In the initial stages of packaging, 3D printing was prioritized. A silicone mold was created using 3D printing, and instead of the conventional injection-type packaging method, a mold was employed to shape only the exterior of the packaging. The PCBs were embedded in the mold, and the process involved filling it with Ecoflex 0030. [7] During the packaging of the three PCBs in this study, there was a potential issue of electrode misalignment due to gaps, leading to a deviation in the position of measurement electrodes. To address this problem, additional silicone support structures were fabricated, aligning the gaps between each PCB to ensure proper adhesion of electrodes to the carotid artery. Additionally, the backside of the packaging allows access to data I/O pins (SWDIO), clock pins (SWDCLK), and battery connection lines (POWER, GND) through an opening. As shown in Fig. 4, this structure facilitates convenient firmware updates and a battery detachment system, enabling an easy charging method.



(a)

(b)

(c)



(d)

Fig. 4. (a) Packaging Exterior, (b) Gap Correction Structure, (c) Front view of the prototype, (d) Rear view of the prototype

B. *Blood Pressure Estimation Result*

The data obtained from the sensors was plotted in MATLAB as shown in Fig. 5. Based on this, blood pressure estimation was conducted by incorporating the equations described earlier. Blood pressure estimation was conducted with a total of 15 sets of data, and based on this, the accuracy of the method was analyzed in Table 1.

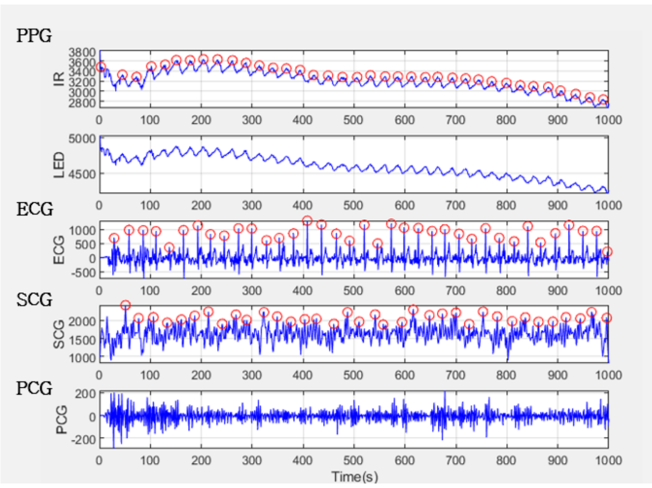


Fig. 5. Cadiac signal data from Four different sensors.

Sex	Age	Height (feet)	Weight (pound)	Actual Ps (mmHg)	Actual Pd (mmHg)	Ps (mmHg)	Pd (mmHg)	Ps Error	Pd Error	Ps Accuracy	Pd Accuracy
M	25	5.7	152.1	126	80	125.1	74.8	0.71	6.50	99.29	93.50
M	23	5.81	169.8	132	77	128	79	3.03	2.60	96.97	97.40
M	22	5.857	169.76	127	73	133	81	4.72	10.96	95.28	89.04
M	28	5.31	182.98	130	80	132	71	1.54	11.25	98.46	88.75
M	23	5.77	132.30	125	76	129	72	3.20	5.26	96.80	94.74
M	21	5.77	154.35	131	74	127	73	3.05	1.35	96.95	98.65
M	23	5.81	167.58	122	79	124.1	75.1	1.72	4.94	98.28	95.06
M	21	5.64	143.33	144	85	130.8	74	10.09	14.86	89.91	85.14
M	23	5.84	187.43	128	78	120.2	77.2	6.49	1.04	93.51	98.96
M	19	5.97	152.15	130	80	134	70	2.99	14.29	97.01	85.71
M	23	5.77	149.94	135.8	69.4	144	89	5.69	22.02	94.31	77.98
M	25	5.31	114.66	114	76	142.87	65.88	20.21	15.36	79.79	84.64
M	23	6.10	176.40	118	80	124.77	74.93	5.43	6.77	94.57	93.23
W	21	5.60	114.66	111	79	105.56	84.54	5.15	6.55	94.85	93.45
W	21	5.09	101.43	102	62	134	69	23.88	10.14	76.12	89.86

Fig. 6. Blood Pressure Estimation Results

TABLE I. BLOOD PRESSURE ESTIMATION ACCURACY ANALYSIS

Metric	Error Rate(%)
Overall Error	7.73
Systolic Error	6.53
Diastolic Error	8.93
Accuracy	92.27

C. *Predicted ECG Result*

A long short-term memory network (LSTM) considering long-term dependencies of accounts is designed to predict ECG data. The model comprises three LSTM layers stacked together, where each layer processes the given sequence data and passes it on to the subsequent layer. For sequence prediction, the output layer was structured using the TimeDistributed layer.

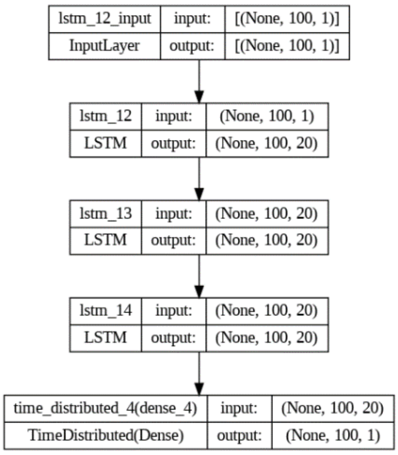


Fig. 7. Model Summay

During the model's compilation stage, the Adam optimizer was chosen, and the Mean Squared Error (MSE) was employed as the loss function. The optimizer's learning rate was set to 0.01, and gradient clipping was applied to facilitate stable training. The training metric for the model is represented by the loss values using MSE, as shown in Fig. 8. Additionally, a plot comparing the predicted and actual ECG for a single sample is presented in Fig. 9. Based on this, it can be observed that the model has been trained to avoid overfitting.

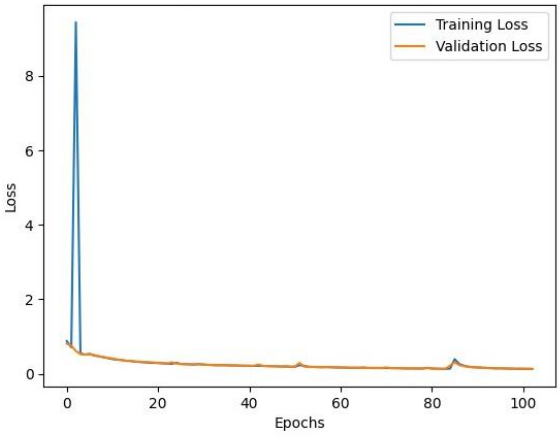


Fig. 8. Training and Validation loss over Epochs

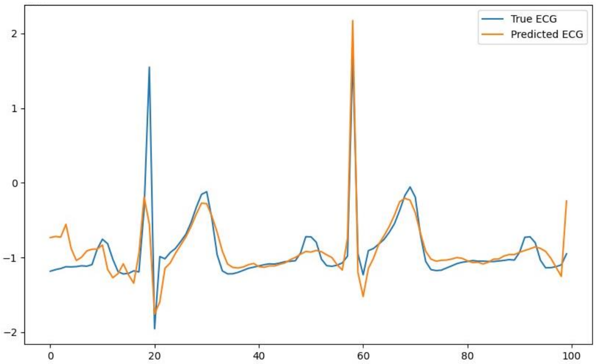


Fig. 9. Actual and Predicted ECG

IV. Conclusion

This comprehensive approach highlights the development of a compact device for measuring various cardiac signals and estimating blood pressure. Specifically, it demonstrated the potential to predict ECG solely using the SCG sensor and, based on this prediction, estimate blood pressure using minimal hardware resources—relying solely on the SCG sensor. Such achievements lay a crucial foundation for further research and applications in the realm of mobile health monitoring systems.

Acknowledgment

This work was supported in the National Research Foundation of Korea (NRF) grant funded by the Korea government. (MSIP; Ministry of Science, ICT & Future Planning, No. NRF-2021R1F1A1049758)

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