Systolic blood pressure measurement algorithm with mmWave radar sensor

JingYao Shi[1], and KangYoon Lee[2*]
[1] Department of Computer Engineering, Gachon University
Seongnam, South Korea
[e-mail: qq490800573@gachon.ac.kr]
[2] Department of Computer Engineering, Gachon University
Seongnam, South Korea
[e-mail: keylee@gachon.ac.kr]
[*]Corresponding author: KangYoon Lee

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Abstract

Blood pressure is one of the key physiological parameters for determining human health, and can prove whether human cardiovascular function is healthy or not. In general, what we call blood pressure refers to arterial blood pressure. Blood pressure fluctuates greatly and, due to the influence of various factors, even varies with each heartbeat. Therefore, achievement of continuous blood pressure measurement is particularly important for more accurate diagnosis. It is difficult to achieve long-term continuous blood pressure monitoring with traditional measurement methods due to the continuous wear of measuring instruments. On the other hand, radar technology is not easily affected by environmental factors and is capable of strong penetration. In this study, by using machine learning, tried to develop a linear blood pressure prediction model using data from a public database. The radar sensor evaluates the measured object, obtains the pulse waveform data, calculates the pulse transmission time, and obtains the blood pressure data through linear model regression analysis. Confirm its availability to facilitate follow-up research, such as integrating other sensors, collecting temperature, heartbeat, respiratory pulse and other data, and seeking medical treatment in time in case of abnormalities.

Keywords: Blood pressure estimation, mmWave Radar, non-contact, Pulse Wave Transit Time

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1. Introduction

Blood pressure is an important parameter for monitoring human health, and it can be used to monitor human cardiovascular functioning. Therefore, noninvasive blood pressure measurement has received considerable attention from the researchers. It is difficult to obtain continuous noninvasive blood pressure measurements through conventional blood pressure measurements that may cause discomfort to the patients. It is difficult to continuously monitor for a long time. Nowadays due to the covid-19 pandemic, non-contact measurement has become even more important because of its inherent characteristics. The radar technology described in this paper can overcome the limitations of conventional contact measurement, such as the measuring distance. Furthermore, the radar technology is not easily affected by environmental factors and has a strong penetration. Compared with non-contact detection techniques, such as infrared and imaging, it is more suitable for monitoring heart beat or pulse wave signals.

Based on continuous wave radar for detecting pulse wave signal, the characteristics of pulse wave signal are determined, the pulse conduction time is calculated, the blood pressure is estimated through linear regression analysis, and high accuracy continuous blood pressure monitoring is attempted. The remainder of this paper consists of the following details:

1. The conventional blood pressure measurement method, the hardware platform of continuous wave radar system, and the principle of pulse wave signal formation are introduced. In addition, a comparative test is designed to verify that the radar measurement signal is a pulse wave signal.
2. Pulse wave characteristics are extracted and pulse wave transit time is calculated.
3. Blood pressure is estimated on the basis of the linear regression model of pulse wave transit time for individual blood pressure measurements and data from the public health database. The accuracy of the algorithm is verified to ensure high-precision continuous blood pressure monitoring.

2. Theory and related work

This section describes the common blood pressure measurements currently available and summarizes the characteristics of each method. The reasons for studying non-contact blood pressure measurements are briefly explained by comparison, followed by a brief description of the radar technology required for non-contact measurements. Finally, according to the characteristics of human pulse and radar technology, the viewpoint of subsequent experiments is presented.

2.1 Advantages and disadvantages of different blood pressure measurement methods

Existing blood pressure measurements are categorized into invasive and noninvasive methods. Noninvasive methods are simpler, faster, require less expertise, have fewer complications, and are less uncomfortable and painful for patients, compared with invasive methods. Noninvasive methods, however, may produce a lower accuracy and are therefore more often used for routine inspection and monitoring. Intensive vascular pressure monitoring through intubation is rarely associated with complications such as thrombosis, infection, and bleeding. Invasive surveillance allows extremely close monitoring of patients because severe bleeding can occur if the line is disconnected. It is commonly used for patients who expect rapid changes in the arterial pressure.

2.1.1 Auscultatory

Auscultation is categorized into manual auscultation and automatic auscultation. Artificial auscultation blood pressure monitors mainly consist of mercury blood pressure monitors and blood pressure monitors. They usually need to be operated by professionally trained personnel because human-oriented auditory and visual causes are likely to produce errors [1]. Auto-auscultation technology is difficult to achieve however, because of the great individual differences between people. Although auscultation is accurate, continuous monitoring over a long time period is also difficult [2].

2.1.2 Oscillometric

When employing this method to measure blood pressure, a high precision pressure sensor is required, and the sensor must be placed in the middle of the artery. A small offset can cause a large error. In addition, complete rest is required during the measurement, and a minor exercise may have a significant impact on blood pressure measurement [3].

2.1.3 Pulse wave velocity (PWV)

There are two mature noninvasive continuous blood pressure measurement methods: arterial tension method and volume compensation method. However, these methods are challenging. They do not solve the problem of the measuring device being bound to the human body and are not suitable for long-term continuous blood pressure measurement and monitoring. As early as 1976, Brain Gribbin et al. were able to monitor changes in blood pressure through changes in the pulse wave conduction velocity; however, they were not able to estimate the blood pressure [4]. In fact, blood pressure measurements based on PWV were obtained by the Japanese scientist Tanaka in the early 1980s; however, the accuracy of blood pressure measurements needs to be improved further [5].

Pulse transit time (PTT) is one of the current research hotspots. PTT is the time between two points of the pulse wave in the artery. The research on PTT method can be divided into three basic cases to determine a stable measurement method for obtaining an accurate PTT. Accurate modeling of the relationship between blood pressure and pulse wave translation time as well as more information on blood pressure are required.

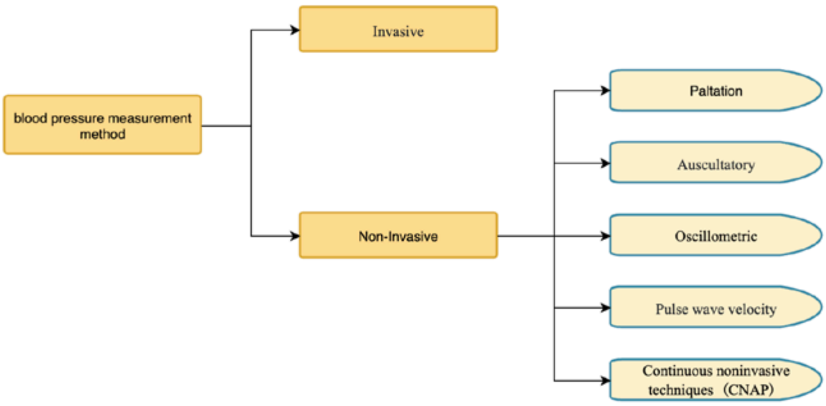

Fig. 1. Summary diagram of blood pressure measurement methods

This paper briefly summarizes the commonly employed blood pressure measurements. Table 1 briefly summarizes the existing blood pressure measurements described above. Most of the existing measurement methods are contact measurement techniques that require multiple sensors to be worn simultaneously; this might cause discomfort in the subjects and affect the physical characteristics of the subject, thereby interfering with the accuracy of measurement. Non-contact sensors can avoid discomfort and any potential interference with the end result. Therefore, this study mainly investigates the acquisition of pulse wave propagation time using non-contact continuous wave radar sensor and employs machine learning linear regression algorithm to analyze the relationship between pulse wave propagation time and blood pressure to predict blood pressure.

Table 1. Summary of blood pressure measurement

Method	**Applicable scenarios (advantages)**	**Limitation**
Palpation	The American Heart Association recommends that palpation be used for estimation before employing the auscultatory method	Only suitable for emergency situations when there is no blood pressure measurement equipment available.
Auscultatory	This method is not affected by calibration errors and drifts that affect other methods.	Certain technical expertise is required to conduct this method.
Oscillometric	This method is suitable for use by untrained personnel and automatic home monitoring of patients.	This method may produce inaccurate readings for patients with heart and circulatory system problems.
Pulse wave velocity (PTT)	This method is for continuously measuring the subject's blood pressure without inflatable arm cuffs.	It may be necessary to calibrate the individual to be measured during the first measurement.
Continuous noninvasive techniques（CNAP）	This method can measure blood pressure continuously and in real time, similar to a standard upper arm sphygmomanometer.	The sensor needs to be attached to the patient's body for a long time that may cause discomfort to the patient.

2.2 Introduction to radar technology

The radar used in this study is millimeter-wave continuous wave radar. Millimeter wave (mmWave) is a particular radar technology that uses short-wave electromagnetic waves. A millimeter-wave radar system consists of a transmit (Tx) and receive (Rx) radio frequency component and analog components, such as a clock. The principle can be roughly summarized as the reflection of the radar-emitted electromagnetic signal blocked by objects on the transmission path during transmission. As shown in Fig. 2, the radar emits a continuous-wave radio frequency signal that returns after being reflected from the object to be measured. The required information can be obtained by analyzing the phase change of the continuous radio frequency signals.

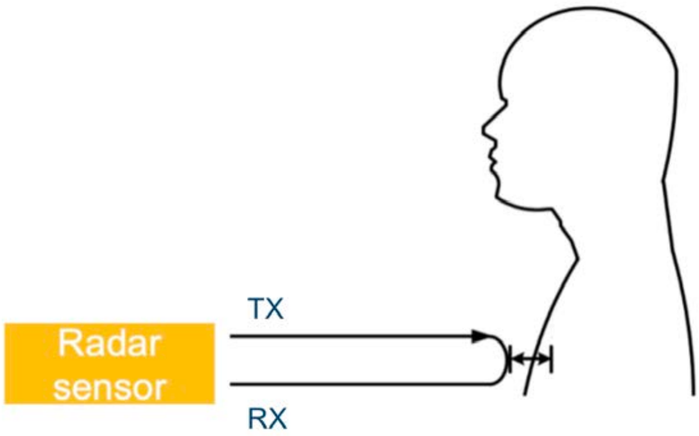

Fig. 2. Schematic of the mechanism of radar

2.3 human pulse relationship between PTT

Pulse refers to the fluctuation of human blood vessels caused by blood flow. The human heart is constantly contracting and relaxing, delivering fresh blood through the blood vessels to the whole body. The beating of the heart causes periodic changes in blood flow, resulting in constant changes in the volume of blood vessels and their pressure on the inner wall, thereby causing the blood vessels to constrict or dilate.

The inflection point on the pulse wave curve represents the characteristic point of the pulse wave that implies that one mechanical process is gradually transforming into another during a cardiac cycle. Therefore, the inflection point of the pulse wave is significant. Extracting the inflection points of the pulse wave and combining the corresponding information could be advantageous for clinical use.

Jiao Xuejun used linear regression equation to determine the relationship between pulse wave conduction time and blood pressure. It was found that the linear regression equation between diastolic blood pressure and pulse wave conduction time was considerably less accurate than that for systolic blood pressure [6,7]. Thereafter, drugs were used to alter the subjects' real-time blood pressure, and an intubation method was chosen to verify the relationship between pulse wave conduction time and blood pressure. The results showed that there was a linear relationship between systolic blood pressure and pulse wave conduction time, but there was no correlation between diastolic blood pressure and pulse wave conduction time [8,9].

In this study, on the basis of previous studies, mmWave radar technology is used to measure the pulse waveform, Calculate PTT data. The waveform data and blood pressure data (systolic blood pressure) from the public health database are combined with linear regression analysis to develop a blood pressure estimation model based on machine learning, High precision blood pressure prediction is realized. To verify the accuracy of the model, the PTT is calculated using the waveform data collected by the radar; thereafter, the blood pressure data is inferred using the developed linear regression model, and the accuracy is verified by comparing with the blood pressure data simultaneously collected by the contact sensor. It is convenient to apply the model to the fields of clinical medical auxiliary diagnosis, family self-monitoring and telemedicine auxiliary diagnosis, and the application prospect is bright. For example, other sensors can be integrated to collect temperature, heartbeat, respiratory pulse and other data at the same time, and added to the ready-made health consultant reference model [10] to facilitate users to continuously observe their own health conditions so they may find abnormalities and seek medical treatment in time.

3. Blood pressure estimation method

Based on the related work, this section mainly describes the method of building a linear model based on PTT to predict blood pressure. The theory of the speed at which the pulse travels through the circulation can be traced back to Thomas Young's work in 1808. The calculation method of PWV is similar to that of sound velocity. In this study, the relationship between pulse pressure and blood flow rate was verified by calculating Moens Korteweg equation. And the subsequent process of calculating blood pressure[11].

3.1 Denoises the original pulse signal and Acquisition of Feature Points

The method used in this paper is to extract the characteristics of pulse wave signals in a small range using the method of wavelet transformation. Wavelet transform is adaptive. Compared with other mathematical methods, wavelet transform is very suitable for non-stationary signals such as pulse wave [12]. After determining each cycle of the pulse wave, the characteristic value is extracted through the modulus maximum and modulus minimum of each cycle of the pulse wave. We suppress high-frequency noise signals on the first and second layers of detail coefficients, and then reconstruct the pulse wave signal. We chose to use the default threshold denoising method. The threshold is generated by the system, the coefficients smaller than the threshold are set to zero, and the remaining coefficients are then taken as the reconstructed signal[13]. In a pulse wave cycle, the process of locating pulse wave feature points is as follows:

1. Perform 4-level wavelet decomposition on the signal.
2. Determine the maximum value of the maximum modulus within one pulse wave cycle and find the adjacent minimum value of the modulus. Then connect the modulo maximum value and the modulo minimum value, find the intersection of the straight line and the horizontal axis, and then find the position of the valley value during the lowest point near the waveform corresponding to the intersection.
3. Continue to use the same method to find the three intersections of the three lines with the horizontal axis. Then, find the position of the peak, dicrotic wave peak, the location of dicrotic wave valley in the vicinity of the waveform corresponding to each intersection point.
4. Finally, four characteristic points of a pulse wave cycle can be obtained: the main peak, the main valley, dicrotic wave peak, dicrotic wave valley.

3.2 Pulse wave transit time and blood pressure

When the blood pressure increases, the arterial wall shrinks, the blood flow velocity accelerates, and the pulse wave conduction time shortens. When the blood pressure drops, the arterial wall relaxes, the blood flow propagation velocity slows down, and the pulse wave conduction time increases [14].

3.2.1 Pulse wave transit time

PWV refers to the velocity of pressure wave propagating along the aortic wall when blood flows out of the heart every time the heart beats. PTT is the velocity at which pressure waves propagate along the aortic wall from one point to another with each beat of cardiac blood.

Ahmed Qasem, from the Department of advanced medicine, Macquarie University, Australia, proposed an individual arterial pulse waveform method for calculating pulse wave conduction time. The measurement results were compared with those obtained via the conventional method to verify the feasibility and accuracy of this method [15].

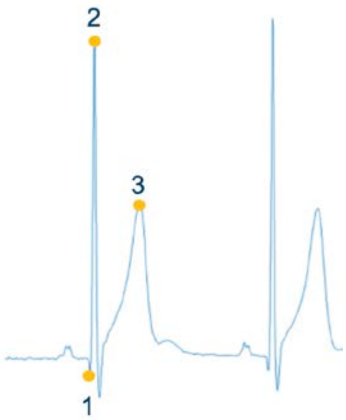

Fig. 3. Characteristic points of pulse wave waveform signal

In this method, the first systolic peak (the main peak) at the starting point of the active pulse wave (the main valley of the previous pulse) is extracted, and its corresponding time (point 1 to point 2) that is recorded as T_1 is calculated. After that, extract the dicrotic wave peak of the pulse wave, that is, the second inflection point of the aortic pulse wave waveform, and its corresponding time (from Point 1 to Point 3) is calculated that is recorded as T_2, as shown in **Fig. 3**.

Accordingly, the pulse wave conduction time PTT can be expressed as

$$PTT = \frac{T_2 - T_1}{2} \tag{1}$$

3.2.2 Relationship between pulse wave transit time and blood pressure

In 1808, Thomas Young regarded blood as an ideal fluid and human artery as a uniform straight thin-walled elastic tube. Ignoring the change of vessel wall thickness, he deduced the calculation formula of pulse wave conduction velocity.

$$PWV = \sqrt{\frac{Eh}{\rho d}} \tag{2}$$

E is the elastic modulus of the artery, is the thickness of the artery wall, D is the diameter of the artery, and blood density ρ Blood can hardly be compressed under normal conditions, so is assumed to be constant, the other three variables are E, ρ , and d, where E is the main factor on which PWV depends.

In 1878, Moens revised the pulse wave velocity formula based on the experimental results of ordinary fluids, and the results were the same as those derived by Korteweg. Now commonly known as the Moens-Korteweg Equation, where K stands for Moens' constant, and when applied to the human aorta, K = 0.8 [16].

$$PWV = K\sqrt{\frac{Eh}{\rho d}} \tag{3}$$

Since the parameters in (3) may vary from artery to artery and are difficult to measure.

Equation (4) based on the method described by Bramwell & Hill, a modification of Moens Kortweg Equation (3) is proposed for the relationship between pressure and volume, or pressure and diameter. These changes are[17]:

1. Arterial compliance (dV/dP) decreases with increasing pressure due to the curvilinear relationship between arterial pressure and volume.
2. Volume V increases with the increase of pressure (arterial dilation), which directly increases PWV.

$$PWV = \sqrt{\frac{V * \ dP}{\rho * dV}} = \sqrt{\frac{r * dP}{\rho * 2 * dr}} \tag{4}$$

The pulse wave conduction time of monomer is linearly correlated with its corresponding blood pressure. The pulse wave conduction distance is S, and the conduction time PTT is inversely proportional to the conduction velocity PWV [18].

$$PWV = \frac{S}{PTT} \tag{5}$$

The existing measuring equipment has limitations in the measurement of human arterial elasticity, and the change of human vascular elasticity is extremely small in a short time, ignoring the minor influence of unmeasurable parameters in blood vessels. According to (4) and (5), it can be concluded that blood pressure is directly proportional to pulse wave conduction time [19].

Substituting Equation (4) (5) into Equation (2) yields Equation (6). The Equation (6) is as follows:

$$\mathrm{P} = \frac{1}{\gamma}[\ln(\frac{\rho d S^2}{aE}) - 2 \ln PTT] \tag{6}$$

Ignoring the internal unmeasurable parameters and deriving from both sides, Equation (6) can be obtained.

$$\frac{dP}{dPTT} = -\frac{2}{yPTT} \tag{7}$$

Namely:

$$\Delta bp = \frac{2}{yPTT} \Delta PTT \tag{8}$$

where Δbp is the magnitude of change in the blood pressure, P stands for trans-wall pressure, y is the characteristic parameter of blood vessel, the general value of which for the human body is 0.016–0.018 mmHg.

3.3 Linear regression model

As discussed above, there is a linear relationship between systolic blood pressure and pulse transmission time. Linear regression is a type of regression analysis that uses the least square function called linear regression equation to model the relationship between one or more independent variables and dependent variables. Linear regression is used to train the model based on the specified training data and subsequently predict when the known characteristics of the selected area meet the linear conditions. Linear regression is the first algorithm in regression analysis that has been extensively studied and widely used [20,21].

In the human body, the change of vascular elasticity is extremely small in the short term. Ignoring the marginal influence of the unmeasured parameters of vascular elasticity, the blood pressure is directly proportional to the pulse wave conduction time and is relatively stable for a period of time. Because the linear relationship between systolic blood pressure and pulse wave conduction time is more obvious, the estimation model of systolic blood pressure (SBP) and pulse wave conduction time can be expressed as follows according to (8):

$$SBP = a + b \times PTT \tag{9}$$

Considering a packet of data as an example, as described in Section 2.1.1, three characteristic points on each pulse wave shape is extracted, the corresponding pulse wave conduction time is calculated, and thereafter, all the pulse wave conduction times are averaged to obtain the pulse wave conduction time corresponding to a packet of data for 10 s. Thereafter, the pulse wave conduction time and the corresponding systolic blood pressure SBP are substituted into (9) to calculate the correlation coefficients a and b.

4. Experimental details

This section describes the process of validating the reliability of sensor models and data comparisons used in real-world measurements and establishing blood pressure prediction models. There is also a process of validating models with a ten-cross validation method.

4.1 Measurement data collection

The radar used in this study is millimeter wave continuous wave radar that is a specific radar technology based on short wave electromagnetic wave. The specific radar model is the IWR-6843AOP radar sensor produced by Texas Instruments. IWR-6843AOP is an encapsulated antenna (AOP) device, which is an evolution of Texas Instruments (TI) single chip radar device series. It integrates an MCU chip with a very small volume, which can analyze the basic radar signal inside, and transmit the data to the upper computer through UART communication.

The contact sensor used for comparison uses a MKB0908 blood pressure sensor. The sensor uses the traditional PPG method to calculate blood pressure data. With higher accuracy. And the data can also be transmitted to the computer through UART.

During measurement, the radar sensor aims at the left arm of the subject for measurement. The object to be measured shall be kept stationary as far as possible, and the radar sensor shall be placed approximately 10–20 cm away from the measurement position to reduce the interference due to other factors for subsequent measurement. Simultaneously, the contact sensor measures the position of the forearm close to the wrist. The comparison shows that the waveforms obtained via contact and non-contact measurements are similar (that is, the waveforms have similar peaks and troughs). The radar sensor particularly collects the waveform data, while the contact sensor specifically collects blood pressure, pulse (waveform), and other data for reference.

Fig. 4. Actual measurement scenarios (Left: Radar / Right: Contact sensor)

Through actual comparison, it is found that the waveform data obtained by radar is similar to that obtained by contact sensor.

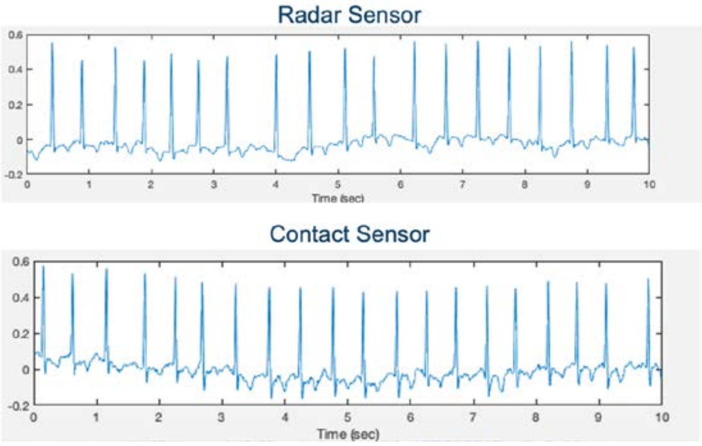

Fig. 5. Comparison of measured data

It can be seen from the comparison that the waveforms are basically the same, except for some detail noise that can be incorporated into the linear model for analysis.

4.2 Linear regression model (public database)

This study uses the MIMIC-III medical database, a large, free, and available database that contains the health data of multiple patients (relevant identity information is deleted). A variety of biological information such as ECG, PPG, blood pressure, heartbeat, and even ABP (an arterial pressure signal) can be found [22,23].

This database allows users to load waveform data into the working area of MATLAB. Here, 100 packets of characteristic parameter data, such as blood pressure value and pulse (waveform), are intercepted from the database corresponding to 10 s. Thereafter, the average value is calculated. The following pictures can be obtained based on statistics using MATLAB.

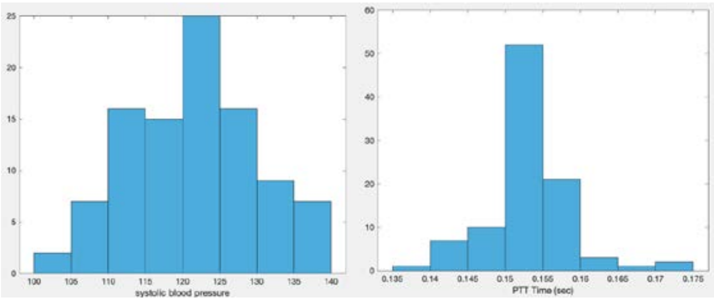

Fig. 6. Data distribution histogram

It can be seen from the distribution map that most of the blood pressure data are concentrated in the range of 110 to 130, and the distribution is roughly uniform. The PTT is the same. Although most of them are concentrated in the interval of 0.15–0.155 s, other intervals also have similar data distribution. The selected data are found to be valid for subsequent analysis.

The correlation between SBP and PTT is linear. The selected data are linearly fitted, and the fitting results are shown in **Fig. 7**. Therefore, the values of parameters a and b corresponding to each data packet can be obtained based on the PTT–SBP fitting curve.

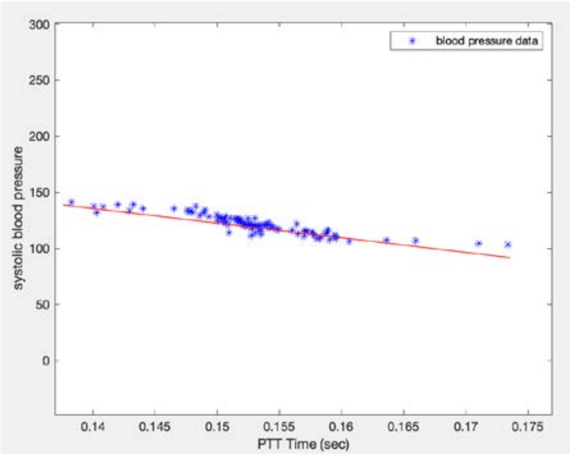

Fig. 7. Linear fitting results

4.3 Linear regression model results

As shown in **Fig. 8**, first the characteristic points of the pulse wave signal are extracted and the PTT value is calculated and substituted into the linear model established based on the public database for analysis; thereafter, the reference to the contact measured blood pressure value is accessed, and the predicted value is output within the available range. In case of a large error, it can be used to improve the prediction model.

We also divide the actual measured data into 50 copies over 10 s (radar test data and the data measured simultaneously by contact sensor are a group). Thereafter, each group of data is imported into the linear model for analysis, and the final results are obtained.

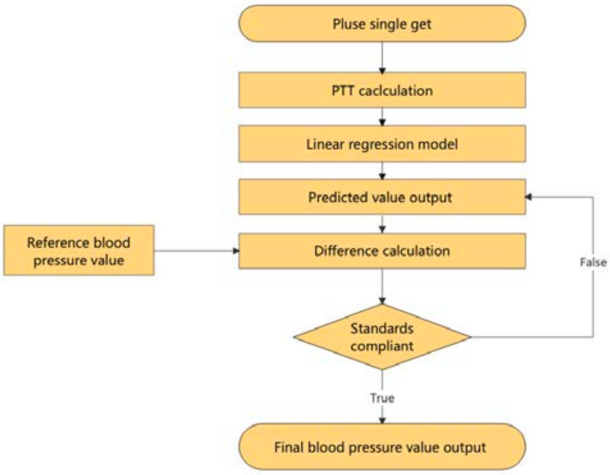

Fig. 8. Flow diagram of the underlying processes of the blood-pressure prediction model

The SBP values calculated on the basis of 10 regression prediction models are mentioned in **Table 2**. Compared with the reference blood pressure values, the error is no more than 5 mmHg. Although the error value of few data is slightly higher, its accuracy basically meets the Association for the Advancement of Medical Instrumentation (AAMI) international standard. The electronic sphygmomanometer standard issued by the American Association for medical device testing (AAMI) is an internationally recognized sphygmomanometer accuracy certification standard. The regression prediction model can effectively calculate the value of SBP [24].

Table 2. Calculation results of linear regression model

	Calculation results	**Reference value**	**calculation error**
S1	115	117	2
S2	109	113	4
S3	116	118	2
S4	114	113	1
S5	115	116	1
S6	108	112	4
S7	117	115	2
S8	115	115	0
S9	119	117	2
S10	108	110	2

4.4 Ten-fold cross-validation

To access the accuracy of blood pressure estimated by the regression model more intuitively, this section introduces the 10-fold cross-validation method. That is, the total sample set s of blood pressure data is divided into 10 groups, namely S1, S2, S3, ..., S10. Here, S1 is the validation sample of the blood pressure model, and the rest are the training samples of the blood pressure model. The model is integrated and verified with the verification sample S1 to obtain the verification error, and the relevant verification indicators of the regression algorithm, such as standard deviation (SD), root mean square error (RMSE), and mean absolute error (MAE), are calculated. Subsequently, considering S2 as the validation sample of the blood pressure model, the above training validation steps are repeated to obtain the relevant validation indicators. The above steps are repeated 10 times, as shown in the figure. The results of validation indicators are summarized in **Table 3**.

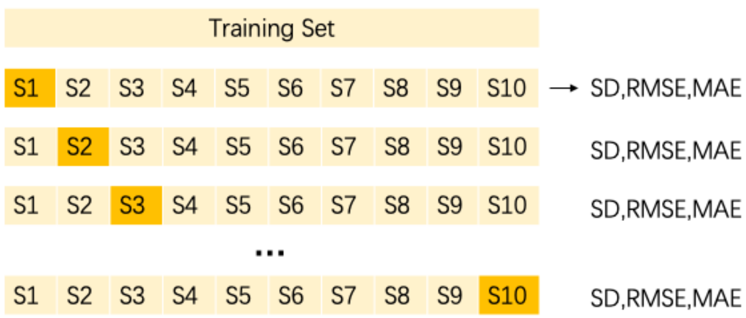

Fig. 9. Schematic of 10-fold cross-validation

The error results of 10-fold cross-validation in this experiment are shown in **Table 3**. Although the error results of the 10-fold cross-validation fluctuate slightly, the overall difference is trivial, indicating the accuracy of blood pressure estimation model. The optimal verification network is selected comparing the results of the 10th verification. The estimation accuracy of the 3rd verification is the best, the error value result of the regression model verification is the best, and the estimation accuracy of the 10th verification is relatively poor, but the accuracy meets the AAMI [24] international standard.

Table 3. Ten-fold cross-validation results

	MAE	SD	RMSE
S1	1.91	1.52	1.84
S2	1.86	1.63	1.77
S3	1.84	1.46	1.70
S4	1.96	1.55	1.82
S5	1.88	1.47	1.73
S6	1.85	1.71	1.75
S7	1.91	1.64	1.79
S8	1.84	1.58	1.83
S9	1.97	1.74	1.95
S10	2.03	1.71	1.94

5. Conclusion

Having conducted the aforementioned experiments, the average deviation of SBP is found to be 2.0 mmHg. AAMI stipulates that if the average error of blood pressure measurement results does not exceed ±5 mmHg, then its accuracy meets the international standards. The k-cross-validation method is also used to verify the accuracy of the regression model in estimating blood pressure. Therefore, it can be seen that the linear regression model can effectively and accurately calculate SBP. However, the relevant parameters need to be calculated separately based on the linear regression algorithm that is computationally expensive and inefficient. The physiological mechanism of blood pressure is complex, and there are few factors that cannot be measured, such as vascular elasticity; therefore, linear regression analysis is not sufficient. In the future, we will attempt to incorporate more body parameters or cardiovascular parameters to improve the blood pressure prediction model further; For example, the addition of more individual parameters (height, weight, BMI) and cardiovascular characteristic parameters (cardiac ejection time, etc.) to build a new blood pressure prediction model. We will also attempt to predict systolic and diastolic blood pressure simultaneously.

Furthermore, we will try to import the prediction model into the radar sensor to realize real-time continuous blood pressure detection to meet the needs of practical application. For example, other sensors can be integrated to collect temperature, heartbeat, respiratory pulse and other data at the same time, and added to the ready-made health consultant reference model to facilitate users to continuously observe their own health conditions so they may find abnormalities and seek medical treatment in time.

References

[1] Yury L. Shevchenko and Joshua E. Tsitlik, "90th Anniversary of the Development by Nikolai S. Korotkoff of the Auscultatory Method of Measuring Blood Pressure," *Circulation*, 94, 116–118, 1996. Article (CrossRef Link)

[2] W. Chen, T. Kobayashi, S. Ichikawa, Y. Takeuchi and T. Togawa, "Continuous estimation of systolic blood pressure using the pulse arrival time and intermittent calibration," *Med. Biol. Eng. Comput.*, 38, 569–574, 2000. Article (CrossRef Link)

[3] K. Yamakoshi, A. Kamiya, H. Shimazu, H. Ito and T. Togawa, “Noninvasive automatic monitoring of instantaneous arterial blood pressure using the vascular unloading technique,” *Med. Biol. Eng. Comput.*, 21, 557–565, 1983. Article (CrossRef Link)

[4] X. Zhang, L. Xu, K. Chen and Z. Zhou, “A New Method for Locating Feature Points in Pulse Wave Using Wavelet Transform” in *Proc. of 2009 WRI World Congress on Computer Science and Information Engineering*, pp. 367-371, 2009. Article (CrossRef Link)

[5] Jacques Blacher, Michel E. Safar, Alain P. Guerin, Bruno Pannier, Sylvain J. Marchais, Gérard M. London, “Aortic pulse wave velocity index and mortality in end-stage renal disease,” *Kidney International*, 63(5), 1852-1860, 2003. Article (CrossRef Link)

[6] Jiao Xuejun, Fang Xingye, “Research on the method of continuously measuring blood pressure using characteristic parameters of pulse wave,” *Journal of Biomedical Engineering*, 19(2), 217-220, 2002. Article (CrossRef Link)

[7] Deng Genqiang, “Research and design of continuous blood pressure measurement system based on pulse wave,” 2017. Article (CrossRef Link)

[8] Youngzoon Yoon, Jung H. Choa, Gilwon Yoon, “Non-constrained blood pressure monitoring using ECG and PPG for personal healthcare,” *Journal of Medical Systems*, vol. 33, pp. 261–266, 2009. Article (CrossRef Link)

[9] Christoph Will, Kilin Shi, Sven Schellenberger, Tobias Steigleder, Fabian Michler, Robert Weigel, Christoph Ostgathe and Alexander Koelpin, "Local Pulse Wave Detection Using Continuous Wave Radar Systems," *IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology*, vol. 1, no. 2, pp. 81-89, Dec. 2017. Article (CrossRef Link)

[10] K. Lee, "Reference Model and Architecture of Interactive Cognitive Health Advisor based on Evolutional Cyber-physical Systems," *KSII Transactions on Internet and Information Systems*, vol. 13, no. 8, pp. 4270-4284, 2019. Article (CrossRef Link)

[11] Bramwell JC and Hill AV, “The velocity of the pulse wave in man” *Proceedings of the Royal Society of London. Series B*, 93(652), 298–306, 1922. Article (CrossRef Link)

[12] I. Daubechies, “The wavelet transform, time-frequency localization and signal analysis,” *IEEE Transactions on Information Theory*, vol. 36, no. 5, pp. 961-1005, Sept. 1990. Article (CrossRef Link)

[13] Xuanwei Zhang, Yazhou Shang, Daoxin Guo, Tianxia Zhao, Qiuping Li and Xin’an Wang, “A More Effective Method of Extracting the Characteristic Value of Pulse Wave Signal Based on Wavelet Transform,” *Journal of Biomedical Science and Engineering*, 09(10), 9-19, January 2016. Article (CrossRef Link)

[14] Liu Zengding, Chen Ji, “Blood pressure estimation model using pulse transit time,” *Chinese Journal of Medical Physics*, 34(2), 199-203, 2017. Article (CrossRef Link)

[15] Qasem A and Avolio A, “Determination of aortic pulse wave velocity from waveform decomposition of the central aortic pressure pulse,” *Hypertension*, 51, 188–195, 2 Jan 2008. Article (CrossRef Link)

[16] Raymond G. Gosling and Marc M. Budge, "Terminology for describing the elastic behavior of arteries," *Hypertension*, 41(6), 1180–1182, 2003. Article (CrossRef Link)

[17] Spronck, Barta; Heusinkveld, Maarten H.G.a,b; Vanmolkot, Floris H.c; Roodt, Jos Op ’tc; Hermeling, Eveliend; Delhaas, Tammoa; Kroon, Abraham A.c; Reesink, and Koen D.a, “Pressure-dependence of arterial stiffness” *Journal of Hypertension*, vol. 33, no. 2, pp. 330-338, February 2015. Article (CrossRef Link)

[18] Akira YAMASHINA, Hirofumi TOMIYAMA, Kazuhiro TAKEDA, Hideichi TSUDA, Tomio ARAI, Kenichi HIROSE, Yutaka KOJI, Saburoh HORI, Yoshio YAMAMOTO, “Validity, Reproducibility, and Clinical Significance of Noninvasive Brachial-Ankle Pulse Wave Velocity Measurement,” *Hypertension Research*, Vol. 25, no. 3, pp. 359-364, 2002. Article (CrossRef Link)

[19] Luo Zhichang and Zhang song and Yang Wenming, “Study on characteristic information of pulse wave waveform,” *Journal of Beijing University of technology*, 22(1), 71-79, 1996. Article (CrossRef Link)

[20] Wang Huiwen and Meng Jie, “Predictive modeling on multivariate linear regression,” *Journal of Beihang University of aeronautics and a*, 33(04), 500-504, 2007. Article (CrossRef Link)

[21] Leo Breiman and Jerome H. Friedman, "Predicting multivariate responses in multiple linear regression," *Journal of the Royal Statistical Society: Series B*, Vol. 59, no. 1, pp. 3-54, 1997. Article (CrossRef Link)
[22] Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L. H., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L. A., & Mark, R. G., "MIMIC-III, a freely accessible critical care database," *Scientific Data*, 3, 160035, 2016. Article (CrossRef Link)
[23] Johnson, A., Pollard, T. and Mark, R., "MIMIC-III Clinical Database Demo (version 1.4)," *PhysioNet*, 2019. Article (CrossRef Link)
[24] George S. Stergiou, Bruce Alpert, Stephan Mieke, Roland Asmar, Neil Atkins, Siegfried Eckert, Gerhard Frick, Bruce Friedman, Thomas Graßl, Tsutomu Ichikawa, John P. Ioannidis, Peter Lacy, Richard McManus, Alan Murray, Martin Myers, Paolo Palatini, Gianfranco Parati, David Quinn, Josh Sarkis, Andrew Shennan, Takashi Usuda, Jiguang Wang, Colin O. Wu and Eoin O'Brien, "A Universal Standard for the Validation of Blood Pressure Measuring Devices," *Hypertension*, vol. 71, no. 3, pp. 368-374, January 31, 2018. Article (CrossRef Link)

SHI JINGYAO received his bachelor's degree from Jiaquan University in 2019. At present, he is a master student in the Department of computer engineering, Gachon University, Seongnam-Si, South Korea. His research interests include healthcare, open platform of Internet of things, artificial intelligence, and sensor development.

KangYoon Lee received B.S. and M.S. degrees from Yonsei University, Seoul, Korea, in 1986 and 1996, respectively, and Ph.D. degree from the department of IT Policy Management, Soongsil University, Seoul, Korea, in 2010. He is currently a Professor at the Department of Computer Engineering, Gachon University, Seongnam-Si, Korea. From 1991 to 2016, he was with IBM Korea, and he was a Lab director of Korea Lab leading Ubiquitous, IoT and Watson Solution Research. His research interests include healthcare, IoT open platform, artificial intelligence, and ambient intelligence.