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Towards wearable blood pressure measurement systems from biosignals: a review

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Abstract: Blood pressure is the pressure by the blood to the vein wall. High blood pressure, which is called silent death, is the cause of nearly 13% of mortality all over the world. Blood pressure is not only measured in the medical environment, but the blood pressure measurement is also a need for people in their daily life. Blood pressure estimation systems with low error rates have been developed besides the new technologies and algorithms. Blood pressure measurements are differentiated as invasive blood pressure (IBP) measurement and noninvasive blood pressure (NIBP) measurement methods. Although IBP measurement provides the most accurate results, it cannot be used in daily life because it can only be performed by qualified medical staff with specialized medical equipment. NIBP measurement is based on measuring physiological signals taken from the body and producing results with decision mechanisms. Oscillometric, pulse transit time (PTT), pulse wave velocity, and feature extraction methods are mentioned in the literature as NIBP. In the oscillometric method of the sphygmomanometer, an electrocardiogram is used in PTT methods as a result of the comparison of signals such as electrocardiography, photoplethysmography, ballistocardiography, and seismocardiography. The increase in the human population and worldwide deaths due to the highly elevated blood pressure makes the need for precise measurements and technological devices more clear. Today, wearable technologies and sensors have been frequently used in the health sector. In this review article, the invasive and noninvasive blood pressure methods, including various biosignals, have been investigated and then compared with each other concerning the measurement of comfort and robust estimation.

Key words: Electrocardiography, photoplethysmography, biosignals, cuffless blood pressure estimation, wearable measurement systems, machine learning

1. Introduction

Deaths related to cardiovascular diseases which correspond to one-third of total deaths have reached about 17 million all over the world. Across the world, 9.4 million people die due to high blood pressure complications every year [1]. The pressure of the blood in the veins is called blood pressure. High blood pressure is a significant risk factor for cardiovascular diseases. High blood pressure can be prevented. Although it can easily be measured, it is generally neglected. When high blood pressure is missed or untreated, heart surgery or dialysis may be required [2]. When blood pressure reaches high values and stays at these values for a long time, continuous high pressure is applied to the vessels. This long-term pressure can lead to damage to the structure of vessels. High blood pressure cannot be noticed and can damage the blood vessels, the brain, the eyes [3], internal organs, and

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the heart. According to the World Health Organization [1], blood pressure disease is called silent, invisible, and lethal [4]. Increasing industrialization, adverse weather conditions, and working conditions lead to stress and stress-related cardiovascular disorders [5]. In every society, blood pressure values of older adults are increasing day by day. The elderly population is more affected by cardiovascular diseases [6] and die from high blood pressure. The effects of blood pressure on young people are also observed as in the elderly. There is an increase in the number of young deaths from high blood pressure in the world. Early diagnosis of high blood pressure is vital. This reveals the necessity of continuous blood pressure measurement. As the blood moves through the veins, it exerts oscillatory pressure on the vessel walls with the effect of the pressure of the heart.

This pressure is comprised of the following parts:
Systolic blood pressure (SBP): Maximum pressure in the arterial wall,
Diastolic blood pressure (DBP): Minimum pressure on the arterial wall,
Mean blood pressure (MBP): Mean blood pressure in the artery wall.

Table 1. American Heart Association blood pressure categories [7]

Blood pressure category	Systolic mmHg	And/or	Diastolic mmHg
	High value		Low value
Normal	Less than 120	and	Less than 80
High	120–129	and	Less than 80
Hypertension Stage 1	130–139	or	80–89
Hypertension Stage 2	140 and above	or	90 and above
Hypertensive crisis (urgent medical advice)	Higher than 180	and/or	Higher than 120

The categories of blood pressure are shown in Table 1. However, the diagnosis of blood pressure should be made by medical experts. Blood pressure may vary according to some environmental factors such as nutrition, stress, emotional state, the pace of work, blood pressure medication, age, weight, obesity [8], white coat effect [9], and similar conditions. Measurements should be made under standard conditions, and long-term measurements are required for diagnosis. Considering these factors affecting blood pressure measurement will help physicians to diagnose and provide appropriate treatment for the right category of blood pressure diseases.

The methods for cuffless blood pressure measurement have been developed in the literature, and the designed blood pressure measurement instruments have been classified with different protocols. Blood pressure measurement devices have been classified according to British Hypertension Society (BHS) [10], American National Standard for Medical Instrumentation ANSI/AAMI SP10: 2002 [11], and European Society of Hypertension (EHS) [12] protocols. Table 2 shows the BHS blood pressure measurement instrument classification.

Table 2. BHS classification criteria.

	$\leq$5 mmHg	$\leq$10 mmHg	$\leq$15 mmHg
Class	Cumulative surface reading		
A	60%	80%	95%
B	50%	75%	90%
C	40%	60%	85%
D	Worse than C		

2. Measurement methods for blood pressure

2.1. Invasive blood pressure measurement

William Harvey (1628) discovered that the heart runs like a water pump, and the blood circulates in the veins [13]. After Harvey's circulatory discovery, the first experimental study on blood pressure was performed by Stephen Hales on animals in 1733 [14, 15]. Hales' animal experiments were invasive [16]; measurements were made with a manometer placed on the vein.

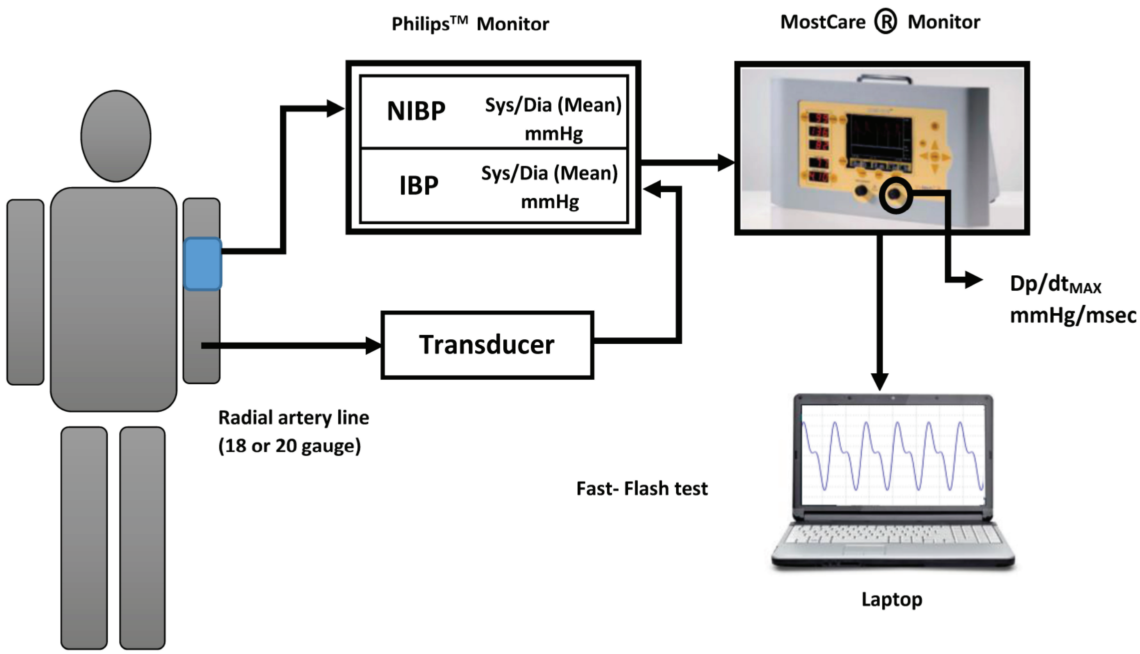


Figure 1. Philips™ monitor for invasive blood pressure (IBP) and noninvasive blood pressure (NIBP) monitoring. [17]

Figure 1 also shows noninvasive and invasive blood pressure measurement methods. In the invasive procedure, a catheter is inserted into the artery with surgical intervention. There is no intervention in the noninvasive method. Invasive blood pressure measurements have been performed by using an arterial catheter insertion method [18]. With the help of a catheter, blood pressure in arteries is transformed into electronic signals. Medical personnel is needed to insert the catheter into the vessel and perform calibration of the device. Measurements are taken in a sterile environment as the catheter is inserted into the vessel. Due to the need for medical experience, technical staff, and sterile environment [19], daily use of the invasive method is not possible.

Poiseuille measured the intravenous blood pressure in 1828 by using the mercury manometer [20]. Carl Ludwig developed the kymograph by drawing on Poiseuille's invention in 1847 [21]. Nowadays, transducers are used to measure blood pressure in the arteries, and the blood pressure information with the transducer can be converted into electrical signals and monitored on monitors [22, 23].

2.2. Noninvasive blood pressure measurement

In 1855 [24], Karl von Vierordt attempted to measure blood pressure without surgical intervention for the first time and made a design. His design could not be used due to some problems. In 1860 [25], Marey improved Karl von Vierordt's design and made it usable. Vierordt's instrument had measurement errors. Basch [26] took more accurate measurements using a device that was attached to a wrist cuff and could be filled with water, for the first time in 1881. In 1896, Riva-Rocci measured the blood pressure with a manometer with an air fillable cuff that he connected to the arm. In 1905, Korotkov [27, 28] listened to the sounds with the help of a stethoscope placed behind the air-filled cuff attached to the arm. In Korotkov's method, when the cuff compresses the arm, the blood flow stops in the artery, and when the air pressure in the shaft begins to be lowered, the sound is heard from the stethoscope. In a specific value, the sound is lost. This sound is called Korotkoff sounds. In the literature, the point that the sound starts to be heard is called systolic blood pressure, and the point that the sound is lost is called diastolic blood pressure. Korotkov's system is still in use today. In Table 3, noninvasive blood pressure measurement methods were compared. Although occlusive techniques provide more precise measurement results, they are not suitable for long-term blood pressure measurements.

Table 3. Comparison of noninvasive blood pressure measurement methods.

	Method	Continuity	Supervision	Occlusive	Accuracy	Periodicity
Occlusive	Auscultation	No	Yes	Yes	Good	Discontinuous
	Oscillometric	No	No	Yes	Good	Discontinuous
	Tonometric	Yes	Yes	Limited	Pure	Continuous
	Volume-Clamp	Yes	No	Yes	Improvement	Semicontinuous
Nonocclusive	PWV-PTT	Yes	No	No	Improvement	Continuous

2.2.1. Noninvasive blood pressure measurement using occlusive methods

Controlled blood pressure measurement with a cuff, a stethoscope, and a barometer: The artery passing through the arm is compressed by the air-inflating cuff, the air is inserted into the cuff, and the blood flow is stopped [29, 30]. While the pressure in the shaft is being reduced, the sound of blood turbulence (Korotkoff sound) is listened using a stethoscope. The starting point of the sound gives systolic blood pressure, and the endpoint gives the diastolic blood pressure. It is a controlled system. A person is needed for the measurement. In each measurement, systolic and diastolic blood pressure values are measured. Time is needed between the measurements to restore the vessels. Measurement results may vary according to the hearing threshold level of the person performing the measuring.

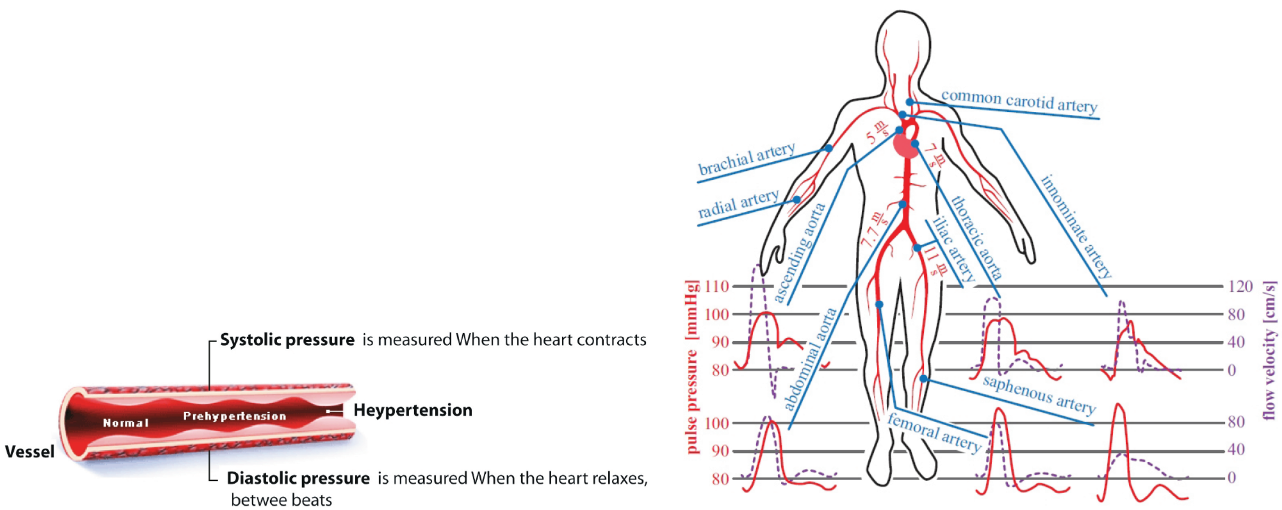
Oscillometric measuring: Using the new technologies and techniques in signal processing, errors stemming from the person who makes measurements in the Korotkov's system have been eliminated. Noncontrolled systems have been developed by locating a pressure sensor in an automatic inflatable cuff which transforms the pressure data in the artery into electrical signals. The measurement devices called oscillometric measurement systems allow people to perform blood pressure measurements by themselves [30–33]. Some decision-making mechanisms are used for converting electrical signals to blood pressure information. In the literature, there are some artificial machine learning models for the estimation of oscillometric blood pressure.

Tonometric measurement: Some pressure is applied on the wrist or arm [34–42]. Blood is not entirely stopped as it is in oscillometric and Korotkov's measurement systems. Pressure sensors measure blood pressure by applying a certain pressure to the measuring point. Since it does not cut the blood flow entirely in the arm, it does not cause any physical problems. Placing the pressure sensor directly on the artery is essential. These measurement systems have some calibration problems.

Volume-Clamp measurement: In the Penáz [43] technique, the pressure is applied to the fingertip using a cuff placed at the fingertip. With the photoplethysmography (PPG) sensor placed under the cuff, the volume of the blood is measured and indicated as pressure information [44–52]. Calibration problems cannot be standardized due to its high systolic value, and it has some physical effects on the veins for long periods of use.

2.2.2. Noninvasive blood pressure measurement using nonocclusive methods

Blood flows in the vessels as a wave. When the heart is contracted, it pumps the blood into the vessel. As a result of this pumping, blood applies pressure on vessel walls. When the heart moves into the relaxation position, the pressure on the vessel walls decreases. The high-pressure point on the vessel wall applied by the blood is called the systolic blood pressure, and the minimum pressure point is called diastolic pressure. This fluctuation in blood pressure excretes through the artery. Moens–Korteweg [53, 54] has discovered that there is a connection between blood pressure and the way the blood travels in the vessel. In the system, two points are taken, and the time between two measurements is calculated. These measurements include electrocardiography (ECG) [55, 56], PPG, phonocardiography (PCG) [57–59], ballistocardiography (BCG) [60–63], seismocardiography (SCG) [64–66], impedance cardiography (ICG) [67–70], use of electrical impedance tomography (EIT) [71], and ultrasonic audio signals [72–76]. Figure 2a shows the normal and high blood pressure of the blood in the vessel. Figure 2b shows the pulse wave velocity (PWV) waveforms formed by the blood in the arteries of the body.



(a) (b)

Figure 2. a) Blood pressure in the vein, b) pulse veins and PWV signals [77].

The R point of the ECG signal is taken as the reference point where the pressure starts at the blood pressure measurements. Other biological signals (ICG, PCG, SCG, IET, BCG, etc.) are taken from the second point through which the blood pressure wave passes through the artery. The time between the maximum point of the ECG signal (R peak-reference point) and the maximum point of the PPG signal gives the systolic blood pressure. The time between the maximum point of the ECG signal (R peak-reference point) and the minimum point of the PPG signal gives the diastolic blood pressure. The time between the maximum point of the reference ECG signal and the minimum point of the second signal gives the diastolic blood pressure. In Figure 3, Poiseuille's law illustrates that the blood flow depends on the diameter of the vessel, the pressure gradient, viscosity, and length of the vessel.

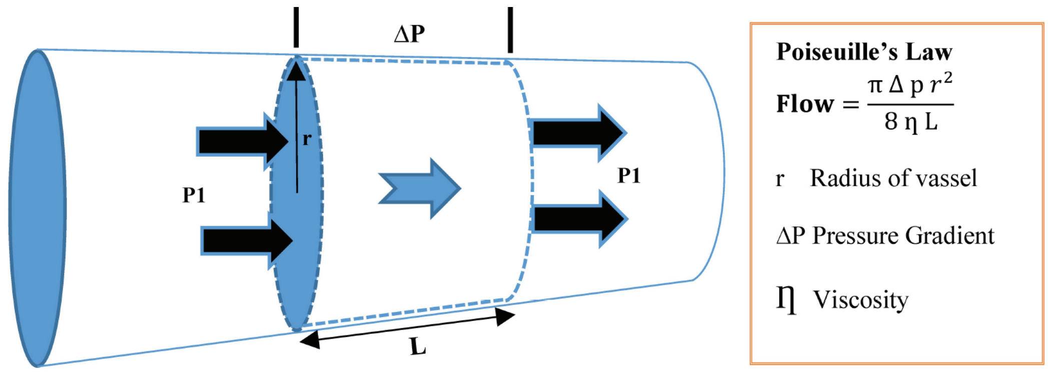


Figure 3. Poiseuille's law.

The relationship between blood pressure and blood flow with Moens–Korteweg is given below in Eq. (1):

$$PWV = \sqrt{\frac{Ein \times h}{2\rho \times d}}. \tag{1}$$

In the PWV calculations, E is the arterial invasion, h is the arterial wall thickness, and d is the vessel diameter at the ρ density of the blood. All of these variables can vary from person to person. It is difficult to take accurate measurements at blood pressure measured with the Moens–Korteweg formula as it is in obstructive methods. PWV changes depending on age, weight, diseases, cardiovascular system disorders, and alcohol and drug use. It is seen that the measurement systems made with PWV are not linear. Based on the features above, the system changes over time. The studies after Moens–Korteweg discovered the similarity between PWV and blood pressure (BP), and have focused on PWV or PTT-BP regression analysis [78], artificial neural networks [79, 80], and deep neural networks [82]. Blood pressure measurement is performed by using the ultrasonic measurement method. However, since the system is complex and not mobilized, it is not suitable for home use outside the healthcare facilities. Since the occlusive vein technique is not used, PWV-PTT is often used [82**?** –85] in clocks, wristbands, wearable health technologies [86] and driver's blood pressure control devices [87, 88]. Because occlusive techniques need a waiting time for the second measurement after the first (a single measurement–single value system), they cannot be used in the cases that require continuous blood measurement. Since the biological signal measurement is performed continuously in PWV-PTT systems, it provides continuous blood pressure information [89, 90]. Figure 4 shows the pulse transit time (PTT) signals that are obtained with biological signals taken at different points of the body. PTT increases as the distance between the measuring points of the biological signals increases.

Figure 5 shows the historical development of blood pressure measurement. Invasive methods are still used today with advanced technologies. Noninvasive methods are still developing in the dimensions of portability, usability, and accurate measurement results.

3. Noninvasive blood pressure measurement system from biosignals

In blood pressure measurement, studies have recently been focusing on noninvasive methods. The most important factors are the necessity of the surgical environment. Since there are several variables in PWV-PTT measurements, the error rate of measurements changes from measurement to measurement; the systems

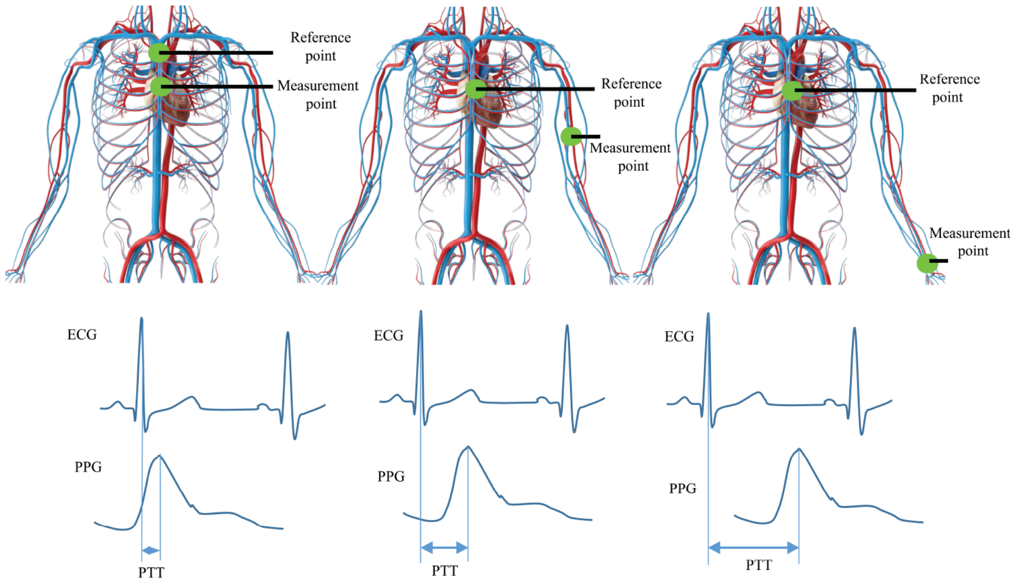


Figure 4. Pulse transit time (PTT) obtained from different points,

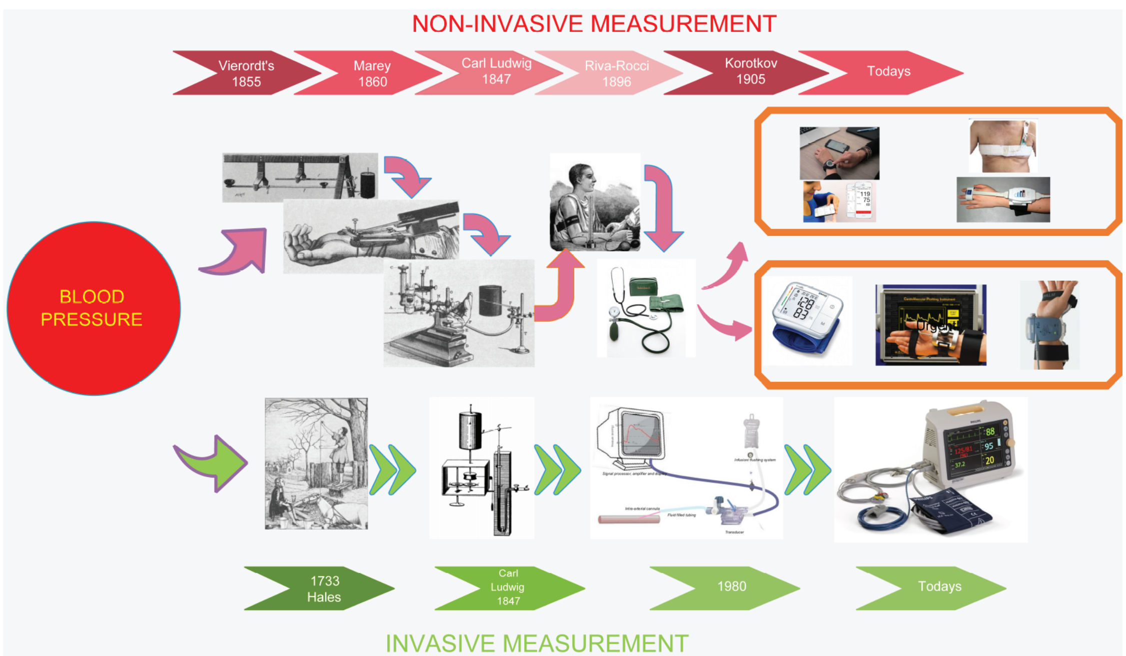


Figure 5. Historical development of blood pressure measurement.

are not linear, and the measurement accuracy is affected negatively. Some of the biological signals such as ECG and PPG, which are directly related to the blood pressure value, can be extracted, and the regression and the machine learning methods, including PWV-PTT, estimate the blood pressure. Figure 6 illustrates a blood pressure measurement block diagram in which occlusive methods are not used. The blood pressure measurement system consists of biological signal reception, pretreatment, segmentation, feature extraction, and training.

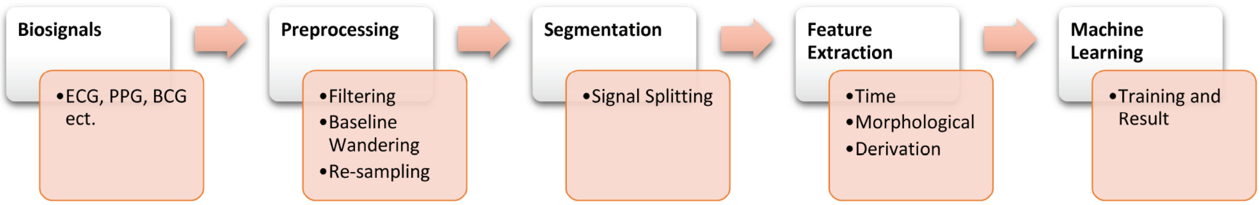


Figure 6. Blood pressure measurement block diagram.

3.1. Acquisition of biosignals

Electrocardiogram ECG: The ECG signal is a graphical recording of the heart's electrical activation with electrodes. The electrical activation of the heart taken from the body surface with electrodes gives information about the heart cycle. The heart cycle is the circulation of blood through the heart and pumped to the artery. In the blood pressure measurement, electrical activity is constituted by contraction of the heart ventricles. This activity is represented by R wave in the ECG signal. The positions of the electrodes used to obtain the ECG signals are important. The positions of the electrode locations are called leads: I, II, III, aVR, aVL, V1, V2, etc. The signal types of the field derivations are also distinctive. In ECG-PPG blood pressure measurements, the R point in the ECG signal is determined as the starting point of PWV. Different ECG leads are used in the studies. In machine learning methods, not only PWV but also different features of ECG signal are used. AgCl jelly [91–93] and dry electrodes are used to detect ECG signals [94, 95]. Textile electrodes are also used in continuous blood pressure measurement methods [96, 97]. Due to their elasticity, the textile electrodes can minimize the noise caused by motion.

Photoplethysmography (PPG): The light source is directed to the body surface, and the photoreceptor detects the reflected light. Hemoglobin (Hb) and oxygen-loaded hemoglobin in the blood absorbs an amount of light emitted from the light source depending on the amount of HbO_2. The difference in wavelengths results in different rates of absorption [98–102]. The photoreceptor is placed in two different positions, next to the light source or opposite the light source. In both positions, the light emitted from the source is retained by the hemoglobin in the blood and oscillates depending on the amount of hemoglobin. The light signal emitted by photoreceptor is converted into an electrical signal, and PPG information is obtained. Figure 7 shows the positions of the photoreceptor. PPG signals are impaired by factors such as body movements, daylight, and breathing. In order to prevent this impairment, the top of the sensor photoreceptor is covered, or a light source in infrared wavelength is used. The impairments of breathing and body movement are balanced automatically by changing the voltage of the light source.

3.2. Preprocessing

In the biological signals taken from the body using noninvasive methods, noise and artifacts are mixed depending on the measurement environment and process. With the electronic filtering method, noises can be decreased but cannot be fully eliminated. Digital filters can purify the signals from the noise and artifacts. Infinite impulse response [103], finite impulse response, wavelet [104], Kalman [105], and similar filters are used for filtering. Shifts may occur in the soles of ECG and PPG signals due to respiration and body movement. Wavelet decomposition [106] and the median filter [107, 108] are used as base correction algorithms. As the ECG and PPG signals are measured, sampling frequency equalization is performed if the sampling frequencies are different. Figure 8 shows the preprocessing block diagram for biosignals.

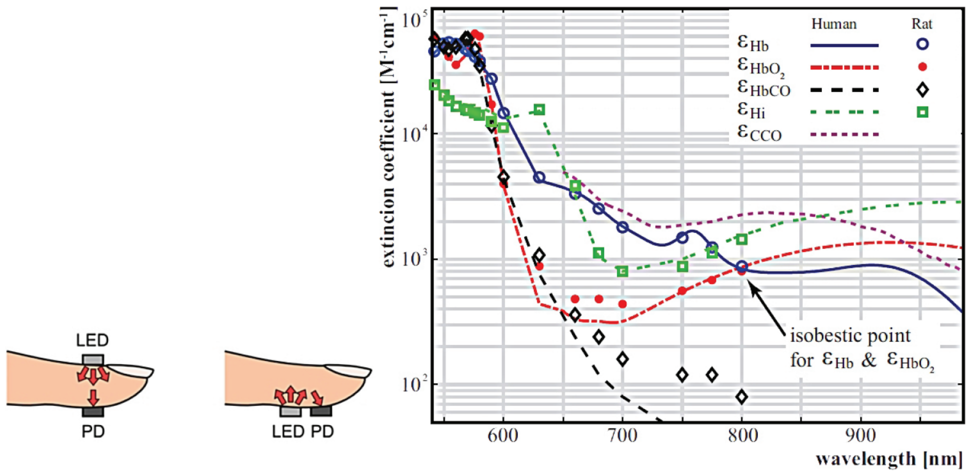


Figure 7. Photoreceptor position and Hb, HbO_2 wavelengths [77].

Figure 8. The flowchart of the generally used preprocessing steps for biosignals.

3.3. Segmentation

The biological signals which are cleaned by preprocessing are measured continuously. These signals need to be separated at specific points to show their features. In studies conducted, the R peak of the ECG signal has been taken as a reference point or segmented to cover the PQRST complex. The PPG signal has also been segmented after the minimum point of the signal.

3.4. Feature extraction

Although PWV-PTT has frequently been used in blood pressure information estimations, it is not sufficient alone. By extracting morphological, derivative, frequency, and time domain features [109–114] from the biological signals taken from the body, higher accuracy rates in blood pressure measurements are obtained. Some of the features are shown in Table 4. Although increasing the number of features increases the accuracy of the measurements, it may slow down the system as the number of entries in the measurement system will increase. The effect of the features on the accuracy of the blood pressure information could be chosen, providing that the maximum efficiency is obtained with various feature selection methods.

Table 4. Feature extraction from biosignals .

Morphological features	Frequency domain features	Derivative features	Time domain features
Maximum	Max frequency	1st derivative maximum point	Distortion
Minimum	Minimum frequency	2nd derivative maximum Point	Openness
Average	Main frequency	1st derivative minimum point	Pulse factor
Dicrotic notch	Standard deviation frequency	2nd derivative minimum Point	Kurtosis
Min–max clearance		Time attributes of the derivative	Mod
Min–max width			Median

3.4.1. Prediction algorithms used for predicting blood pressure using biosignals

Thanks to current technological developments and new algorithms, estimations with high accuracy can be possible. In machine learning methods, it is provided to produce output values for different inputs by training the corresponding output values of certain input values. Models such as random forest [115, 116], regression tree [117], support vector machines [118], K-nearest neighbors, and deep learning [119] are used in the analysis of blood pressure measurements. There is a standard of IEEE on wearable blood pressure gauges [120]. The systems using a machine learning method in blood pressure measurement are still currently researched.

4. Selected works in the blood pressure measurement from biosignals

There are oscillometric, PWV-PTT, and feature extraction-based approaches in the noninvasive measurement of blood pressure. In the oscillometric method, the blood vessel is occluded and then opened gently; the pressure applied by the blood to the vessel is taken by using sensors. Feature extraction is to use different features such as the heart rate (HR) which characterizes blood pressure information from biological signals and the PWV which is the spreading speed of blood in the vessel, to measure blood pressure in different models. Machine learning methods have been frequently used in the health sector. In this study, machine learning methods that use oscillometric and biological signals have been compared.

4.1. Machine learning methods used in occlusive blood pressure measurement

The pressure of the blood is measured by detecting the pressure applied by blood to the vessel walls and converting them to electrical signals [121–123]. Different from the method in which the stethoscope and barometer are used, the intravenous pressure is provided to produce results with decision mechanism. The blood pressure is converted to the electric signals by the pressure sensors attached on the cuff oscillates. This oscillation starts at a certain pressure point and disappears after a certain point. The point at which the oscillation starts gives the systolic blood pressure and the point where it ends gives the diastolic blood pressure. In the measurement of oscillometric blood pressure, the blood pressure points are determined by taking the envelope of the oscillation of the electrical signal generated at the output of the pressure sensor. The signal, which makes oscillometric oscillation, is sent to decision making mechanisms by subtracting the features such as the envelope, baseline and upper envelope, slope of the envelope, and surface of the envelope. Since the change in blood pressure has a nonlinear structure, it is difficult to define it with mathematical models. Instead, artificial neural networks or machine learning models are used. Table 5 shows the oscillometric blood pressure measurement methods, machine-learning model, and their features.

The most critical problem in the measurement of blood pressure with the oscillometric method is to stop the blood flow in the arteries. When the blood flow is stopped, the measurement can be taken once. In order to measure for the second time, the vessel must come back to the normal position, and the blood flow must return to normal. Another disadvantage is the feeling of discomfort in the place where the cuff exerts pressure.

4.2. Machine learning methods used in nonocclusive blood pressure measurement

PWV-PTT method is frequently encountered in the literature, but the measurements do not give the desired results. Since the blood pressure is in the nonlinear structure, PWV-PTT is not enough in itself. As the features derived from biological signals such as ECG, PPG, and SCG are trained with the machine learning methods, the accuracy of the blood pressure measurements becomes higher. As shown in Table 6, the blood pressure

Table 5. Machine learning methods used in blood pressure measurement by occlusion

Models	Features	Envelope Type	Reference
Neural network	Morphological, derivative	Baseline-upper envelope	[124]
PCA-FFNN	PCA	Baseline-upper envelope	[125]
Adaptive-neuro-fuzzy inference (ANFIS)	PCA	Baseline-upper envelope	[126]
FFNN (feedforward NN)	Morphologic features	Baseline-upper envelope	[127]
FFNNs	Morphologic features, time	Baseline-upper envelope	[128]
NN/ANFIS	Morphological	Baseline-upper envelope	[129]
DBN-DN	Morphological	Baseline-upper envelope	[130]
CNN	-	Time-freq. images	[131]
Deep Boltzmann Regression	Gaussian fitting, morphology, age..	Baseline-upper envelope	[132]
ANN	Morphological features	Envelope	[133, 135]
Gaussian mixture model	Morphological, time	Baseline-upper envelope	[134]

is measured by using the Random forest, support vector regression, decision tree AdaBoost, artificial neural network, neural network long short-term memory (LSTM), and similar machine learning methods.

Table 6. Machine learning methods used in nonocclusive blood pressure measurement.

Method	Features	Biological signal	Calibration	Reference
Regression	PTT (Pulse transit time)	ECG,PPG	Necessary	[136]
		ECG, PPG, ICG	Necessary	[137]
		PPG, APG	Necessary	[138]
		PPG, PCG, ECG	Necessary	[139]
		PPG, dPIR	Necessary	[140]
		PPG, PCG, FSR	Necessary	[141]
	PWV (Pulse wave velocity)	ECG,PPG	Necessary	[142]
		PPG, PPG	Necessary	[143]
	PAT (Pulse arrival time)	ECG,PPG	Necessary	[90]
	PPTT (Peripheral pulse transit time)	ECG,PPG	Necessary	[144]
	MSTT(Mean slope transit time)	PPG	Necessary	[145]
Convolution	NPMA(N point moving avarage)	PPG	NECESSARY	[146]
Data mining	PTT (Pulse transit time)	PPG, ECG, 1.st Dppg, 2.st Dppg	NO	[147, 159]
Artificial neural network	Time, width	PPG	NO	[148–150]
	Time	PPG	NO	[151]
	Window	PPG	NO	[152]
	Time, frequency	PPG	NO	[153]
	Time	BMI, PPG, age, sex	Made	[154]
	Multitaper method (MTM)	PPG	NO	[155]
	TIME	ABP	NO	[156]
LSTMN (Long short-term memory networks)	Time features	PPG, ECG	NO	[82]
	Window	PPG	NO	[157, 160–162]

PWV-PTT and PAT are used in regression analysis. PWV-PTT, time, and frequency domain features are used to measure blood pressure with artificial neural networks. By using at least two of the PWV-PTT biological signals, the path taken by the signals in the arteries is calculated, and the blood pressure is measured. Some artificial neural network studies have been used in the training of the neural network in physiological variables as well as biological signals. The neural networks in which the LSTM model is used, sorting training is performed as the features in the history of the signal is learned. In this way, the system will give the forgetting reflex to the sudden refractions, and the accuracy of the model will be raised. Regression analysis requires calibration in blood pressure measurement. The need for calibration is because blood pressure has nonlinear structure, and many variables change the blood pressure measurement. There is no need for calibration in artificial neural networks because the network is trained by the features extracted from biological signals beside the nonlinear variables such as PWV-PTT. When regression analysis is performed in PWV-PTT and biological signals, although the accuracy of blood pressure measurements is high, the related studies are still in the research phase.

5. Comparison of invasive and noninvasive blood pressure measurement methods

Blood pressure measurement is divided into two categories of invasive and noninvasive methods, both of which are still used today. The invasive methods are used in hospitals, and the noninvasive methods are used to measure blood pressure daily at home, office, and medical settings. Although invasive blood pressure measurement methods give the most accurate results, the negative aspects of the system are the necessity of taking measurements with medical equipment and personnel supervision. Nowadays, blood pressure measurement is performed in the hospital environment under the supervision of specialists. In the invasive procedure, a catheter is inserted into the artery, and a pressure sensor measures the blood pressure. The blood pressure information transferred to the pressure sensor via the catheter is converted to electrical signals. The signals from the pressure sensor are transferred to the measuring device, and the blood pressure information is displayed. Blood pressure information can be monitored continuously in the patient monitor and other imaging devices in the invasive method. Since the catheter is inserted through surgical operation, a sterile environment must be provided. However, the risk of infection always exists. Invasive blood pressure measurement may lead to traumas in people who have cardiovascular problems and who have impaired biomechanical cardiovascular parameters. Subcutaneous and skin bleeding may also occur in invasive blood pressure measurements. People with impaired biomechanical cardiovascular parameters may experience rapid blood loss due to nonstop bleeding and pressure in the arteries. Noninvasive blood pressure measurement models are divided into two categories: oscillometric and nonobstructive systems (PWV-PTT and biological signal feature-based). In systems obstructing the vessel, the artery in the arm or wrist is compressed with a cuff, and the blood flow is stopped. When the pressure of the cuff is lowered gradually, the blood forms turbulence in the arteries. These sounds are listened using a stethoscope, and the point where the sound begins shows the SBP and the point where the sound ends shows the DBP. These systems using stethoscope and pressure gauge are controlled systems. A controller is needed to take the measurement. Today, people can measure their blood pressure on their own. A pressure sensor is inserted into a cuff connected to the arm or wrist, and the pressure of the cuff is increased and slowly reduced. The oscillating signal is generated in the pressure sensor. It is called oscillometric because the pressure sensor inside the cuff has oscillation. The envelope of the oscillation signals, which are converted into electrical signals by the pressure sensor, is determined.

The features of the obtained envelope are subtracted, and the blood SBP and DBP values are measured. The studies in the literature are based on finding the features that describe the obtained envelope best and to have highly accurate blood pressure measurements by using machine-learning methods. Although the measurements are highly accurate, because the cuff stops the blood flow in the arteries, it causes negative consequences for people who have problems in the cardiovascular system. The most significant disadvantage is that the measurements cannot be made continuously. In one measurement, only one SBP and DBP value can be taken. There must be some time for the second measurement. The squeezing by the cuff on the arm creates a discomfort. The arm is compressed to absolute pressure, and the cuff stops the blood flow in the artery. The nerves moving from the arm to the hand are also squeezed between the vessels and muscles. In long-term compressions, neural conduction is impaired, and it may cause neural tube defects when used frequently.

In the measurement systems that do not obstruct the vessel, the blood pressure is measured by subtracting some features from the biological signals (ECG, PPG, SCG, etc.) as well as PWV-PTT. Some systems only use PWV-PTT, as well as systems using feature extraction from biological signals. PWV-PTT has been started to be used after it was found that blood pressure in the blood vessel is related to the movement of the blood in the vessel. As the blood emerges from the heart and proceeds through the vein, it applies different amounts of pressure to the vessel walls. Moens–Korteweg showed that blood pressure depends on the density of the blood, the vessel diameter, the vessel thickness and the elasticity of the vessel. PWV-PTT is the measurement of blood pressure which uses the measurements taken from two points in the arteries. Measurements are made using signal pairs such as ECG-PPG, ECG-SCG, ECG-ICG, and PPG-PPG. The features extracted from the biological signals are also used in blood pressure measurement. They are used in the regression analysis as well. The biological signaling characteristics trained in artificial neural networks provide high accuracy in blood pressure measurement. The main problem of the nonobstructive systems is that the blood pressure has a nonlinear structure and PWV-PTT changes from person to person. The blood pressure measurements that do not block the vessels are still being studied. The studies have not reached any international standard yet.

The blood pressure measurement systems that do not block the vascular access have begun to be used in wearable technologies. Wearable technologies come to the forefront in the performance measurements of athletes, in space surveys, and follow-up of patients suffering from tension. Their continuous measurement capabilities and being wearable and transportable make the blood pressure measurement systems that do not block the vessel useful. Since the vessel is not blocked, no discomfort can be mentioned.

6. Discussion and future directions

In the measurement of blood pressure, in invasive systems, improving the pressure sensor connected to the catheter, improving the measurement technologies, and the designs of displays are being investigated. Instead of manual systems, more automatic systems have been used. Another research area is the autonomous systems, which make the calibration themselves. In noninvasive systems, although the techniques that obstruct the vascular pathway are not being able to make continuous measurements and their negative comfort effects, they are more suitable for home use since they provide more accurate results. The unsupervised systems have been improved and become widespread. Showing blood pressure values on display, audible warning systems, unsupervised blood pressure measurement has increased the home use of obstructive systems. When the envelope of the oscillometric signal is better characterized and more accurate measurements are taken, trust in oscillometric systems will increase. In nonobstructive systems, improving the sensors used in the measurement of biological signals, the designs of the electronic and the digital filters used, the performances of the trained networks will affect the accuracy of blood pressure measurement. Being continuous, wearable, and portable make the nonobstructive systems more preferable. Table 7 presents the performance measures of machine learning methods used in nonocclusive blood pressure measurement. Table 8 shows the performance measures of machine learning methods used in occlusive blood pressure measurement.

As can be seen from Table 7, amongst the machine learning methods used in SBP and DBP nonocclusive blood pressure estimation, the performance of LSTM network [155] is high. In Table 8, convolutional neural network [131] and deep Boltzmann regression [132] provide good results for predicting SBP and DBP with machine learning methods used as occlusive blood pressure measurement.

The BHS and ANSI standards for blood pressure measurement devices are established. Blood pressure measurement devices were grouped as A, B, C, D classes in BHS. If a device is in group A, it means that the

Table 7. The performance measures of machine learning methods used in nonocclusive blood pressure measurement.

Measured criterion	Systolic blood Pressure (SBP)	Diastolic blood Pressure (DBP)	Reference
Mean error ± (Standard deviation)	0.07(±1.46)	–0.14(±1.72)	[135]
Mean ± (STD)	–2.6256(±6.7459)	–0.7901(±6.1777)	[136]
Mean ± (STD)	2.13(±5.32)	N/A	[138]
Mean ± (STD)	0.12(±6.15)	1.03(±5.15)	[139]
Mean ± (STD)	3.22(±8.02)	3.13(±4.82)	[140]
Mean ± (STD)	7.47(±11.08)	3.56(±4.53)	[141]
Mean ± (STD)	8.7(±3.2)	4.4(±1.6)	[142]
Mean Error	6.71	4.54	[144]
Mean ± (STD)	–0.91(±3.84)	–0.36(±3.36)	[145]
Mean ± (STD)	–1.148(±5.79)	–1.194(±5.29)	[147]
Mean ± (STD)	6.86(±8.96)	6.34(±8.45)	[148]
Mean ± (STD)	2.32(±3.7)	1.89(±2.8)	[149]
Mean ± (STD)	4.5(±6.13)	3.4(±3.37)	[150]
Mean ± (STD)	3.8(±3.46)	2.21(±2.09)	[151]
Root mean square error	0.784	0.489	[152]
Mean ± (STD)	2.91(±3.76)	2.76(±1.94)	[155]
Root mean square error	2.751	1.604	[156]
Root mean square error	52.906	32.558	[157]
Root mean square error	3.63	1.48	[158]

Table 8. The performance measures of machine learning methods used in occlusive blood pressure measurement.

Measured criterion	Systolic blood Pressure (SBP)	Diastolic blood Pressure (DBP)	Reference
Standard deviation (STD)	5.08	6.09	[124]
Standard deviation (STD)	5.98	7.02	[125]
Standard deviation (STD)	10.258	7.7	[126]
Standard deviation (STD)	9.9	7.34	[127]
Standard deviation (STD)	4.88	10.02	[128]
Standard deviation (STD)	5.81	5.78	[129]
Standard deviation (STD)	6.35	5.28	[130]
Standard deviation (STD)	3.7	3.2	[131]
Standard deviation (STD)	1.6	1.1	[132]
Standard deviation (STD)	13.1	7.3	[134]

device makes sensitive and accurate measurements. According to ANSI, a blood pressure measurement device should have a maximum ±5 mmHg error in the measurements. The blood pressure measuring devices designed should be evaluated according to their continuous measurement, wearability, portability, speed, and comfort features. Nowadays, blood pressure can be measured via mobile phones, watches, wristbands, T-shorts, hats, headgears, dresses, and belts. In the future, dissemination of blood pressure measurement will help to decrease the deaths due to hypertension.

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