Journal of Medical Systems (2019) 43: 24
https://doi.org/10.1007/s10916-018-1138-8

PATIENT FACING SYSTEMS

Continuous Blood Pressure Monitoring as a Basis for Ambient Assisted Living (AAL) – Review of Methodologies and Devices

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Received: 13 March 2018 / Accepted: 9 December 2018 / Published online: 2 January 2019

Abstract
Blood pressure (BP) is a bio-physiological signal that can provide very useful information regarding human's general health. High or low blood pressure or its rapid fluctuations can be associated to various diseases or conditions. Nowadays, high blood pressure is considered to be an important health risk factor and major cause of various health problems worldwide. High blood pressure may precede serious heart diseases, stroke and kidney failure. Accurate blood pressure measurement and monitoring plays fundamental role in diagnosis, prevention and treatment of these diseases. Blood pressure is usually measured in the hospitals, as a part of a standard medical routine. However, there is an increasing demand for methodologies, systems as well as accurate and unobtrusive devices that will permit continuous blood pressure measurement and monitoring for a wide variety of patients, allowing them to perform their daily activities without any disturbance. Technological advancements in the last decade have created opportunities for using various devices as a part of ambient assisted living for improving quality of life for people in their natural environment. The main goal of this paper is to provide a comprehensive review of various methodologies for continuous cuff-less blood pressure measurement, as well as to evidence recently developed devices and systems for continuous blood pressure measurement that can be used in ambient assisted living applications.

Keywords Blood pressure · Electrocardiogram · Photoplethysmogram · Ambient assisted living · Signal processing

Introduction

Blood pressure (BP), defined as the pressure made by circulating blood upon the walls of blood vessels, is an important biomarker of cardiovascular health and indicator for general health of a person [1]. It is considered as one of the most important vital signs of the cardiovascular system [2]. Blood pressure can variate due to some physical activity, anxiety, medication and different emotions. Frequent changes in blood pressure can be a sign of some health issue, especially if they are accompanied by an increased blood pressure. High blood pressure or hypertension, presents a global public health issue. It is the most common cause of death and disability in the world, and a major risk factor for aneurysms of the arteries, stroke and peripheral arterial disease [3, 4]. According to World Health Organization (WHO) report, high blood pressure directly or indirectly causes deaths of nine million people every year [5]. Hypertension rarely causes symptoms in the early stages, so most of the patients with hypertension are not even aware of its existence. Those who are diagnosed usually not have access to early-stage treatment and therefore cannot successfully control their illness over the long term. Having high blood pressure for an extended period of time can damage the vital organs such as kidneys, brain, heart, eyes, or viscus. Because of this, hypertension is also called a silent killer [6]. Daily measurement and monitoring of blood pressure is crucial for early detection of health problems especially heart problems and stroke.

Blood pressure is usually represented with three values: systolic (SBP), diastolic (DBP) and mean arterial pressure (MAP). Systolic pressure, is the blood pressure made on the wall of blood vessels while the ventricles squeeze pushing blood out to the rest of the body. The SBP is the maximum pressure that occurs when the blood is pumped from the left

This article is part of the Topical Collection on *Patient Facing Systems*

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ventricle into the aorta. Diastolic pressure is pressure made on the blood vessel walls as the heart relaxes. The DBP is the minimum pressure that occurs when the blood flows from the atria to the ventricles. Mean arterial pressure is defined as the average pressure in arteries during one cardiac cycle. MAP is usually calculated using the following equation:

$$MBP = 1/3 \times (SBP + 2 \times DBP)$$

Possible methods for measuring BP

Two approaches exist for measuring blood pressure: invasive and non-invasive. The invasive method uses a catheter, which is a thin flexible tube inserted into the artery. Measuring BP invasively requires experts such as physicians and doctors to conduct the measurement and monitoring. It is very accurate, but is usually restricted to hospital settings, for monitoring a high-risk surgical patients and patients in the Intensive Care Unit [7].

As for non-invasive BP measurement, there are various techniques that provides either intermittent or continuous readings. The standard way for arterial BP measurement is using mercury sphygmomanometer. This technique is used more than 100 years, and is still one of the most common method for measuring BP. It uses an air-cuff, placed on upper arm of the patient, which is slowly inflating in order to occlude the blood flow in the artery. While the cuff is slowly deflated, the Korotkoff sounds are detected with a stethoscope placed over the brachial artery of the patient. The cuff pressures at which the first Korotkoff sound is detected represent a SBP, while the cuff pressures at which the fifth Korotkoff sound is detected is the DBP. Because of this, the technique is also known as the auscultative technique [8]. BP can be easily changed from minute to minute, therefore, it is necessary to chart the results over time in order to get an accurate assessment.

Oscillometry is another noninvasive intermittent BP measurement technique that uses an inflatable cuff placed on the arm or wrist of the patient to occlude the blood flow. Unlike the previous technique, where the Korotkoff sounds were detected, this uses a pressure transducer to record the pressure oscillation, during the progressive deflation of the cuff. The pressure at which a maximum oscillation is detected corresponds to MAP, while the SBP and DBP are estimated from the MAP and oscillation pattern, according to various empirical algorithms [9].

A continuous 24-h BP monitoring is necessary and has been intensively used in clinic for hypertension management [10]. For continuous noninvasive BP measurement, a tonometry or the volume-clamp method can be used. Tonometry, is a vascular unloading technique that uses a sensor placed over the radial artery for recording the arterial waveforms. By analyzing these waveforms, systolic and diastolic blood pressure as well as other clinically useful information can be obtained. In order to obtain a stable blood pressure signal, the tonometry sensor must be protected against movement and other mechanical artifacts [11]. The volume-clamp method (based on the work of Peňáz [12]) measures finger arterial pressure with an inflatable cuff combined with an infrared plethysmograph, used to measure the diameter of the artery in finger. The infrared light, emitted by the plethysmograph is absorbed by the blood, while the light detector detect the signal caused by pulsation of arterial diameter during a heartbeat. The pressure in the cuff is adjusted to keep the diameter of the finger artery constant. Changes in cuff pressure is related to blood pressure, so by analyzing these changes and using various algorithms, systolic and diastolic BP is obtained. Similar to tonometry, the volume-clamp method is also sensitive to motion, and cannot be used for BP measurement during normal daily activities. Also, some patient may feel discomfort at the fingertip where the cuff is place, so it is recommended to change the cuff to another finger after a certain period of time. Continuous BP monitoring methods are relatively expensive, compared to conventional intermittent methods, which is the main limitation for their usage.

Technological advancements in the last decade have created opportunities for the appearance of various Ambient Assisted Living (AAL) systems and applications for facilitating health-related care [13]. However, in order to check a person's blood pressure during unexpected situations and to obtain continuous measurements, there is a need for a portable, convenient device or apparatus, which is easy wearable and doesn't create an additional load on the user for everyday use [14]. Recent developments in embedded systems, mobile computing and wireless networks have made cuff-less continuous BP monitoring possible, even outside of the hospitals. Developed electronic systems, products and services, designed for assisting and supporting people in everyday life, can enormously encourage AAL as a way for improving quality of life for people living in their natural environment, regardless of their age. This new approach can also improve the management of the chronic disease through encouraging lifestyle changes and making effective early detection and treatment of many healthcare problems before they need costly emergency intervention. There is an urgent need of new monitoring systems which can include new sensor technologies, algorithms and ambient intelligence that are capable to deal with monitoring patients, conveniently and discreetly at their homes, while performing their daily activities without significant disruption to their comfort or lifestyle [15–17].

The main goal of this paper is to provide a comprehensive review of various methodologies for continuous cuff-less BP measurement, as well as to evidence recently developed devices and systems for continuous BP measurement in AAL applications.

Methodologies for continuous cuff-less BP measurement

With advances in computing power and digital signal processing as well as the growing need for personal health monitoring products, computer-based (automatic) blood pressure assessment and wearable sensors for continuous non-invasive BP measurement have received significant attention. These trends have also incited development of new methods that not only support the popular oscillometric technique but, also provide BP estimation from electrocardiogram (ECG) signals, photoplethysmogram (PPG) signals, or their combination in order to obtain more precise results [18].

Cuff-less noninvasive BP estimation methods are intensively researched in the last decade. Several research groups have developed cuff-less wearable BP monitoring devices that allow patients to continuously monitor BP without interfering with their daily activities [14, 15, 19–23]. Depending on the input signals used for BP derivation these methodologies can be classified in three categories:

1) BP estimation from ECG and PPG signals
2) BP estimation only from PPG signals
3) BP estimation only from ECG

Electrocardiography (ECG) is the process of recording the electrical activities of the heart over a period of time. It is a non-invasive, painless test, very commonly perform to detect cardiac problems or to monitor the heart's status in many situations. ECG usually uses sensors (electrodes), placed over the skin that can detect the electrical signals from the heart. Signals from these sensors are brought to simple electrical circuits with amplifiers and analogue–digital converters. ECG consist of three waveforms: P wave, QRS-complex, and T-wave (Fig. 1). The P wave looks at the atria, the QRS-complex looks at the ventricles and the T-wave evaluates the recovery stage of the ventricles while they are refilling with blood. Like any electrical signal, ECG can be susceptible to different kinds of noise, caused by other body muscles movements or poor contact of electrodes or noise arising from the equipment itself. Removal of unwanted noise is one of the main challenges in ECG signal preprocessing part [24–27]. Various techniques are used for removing these artifacts, like: adaptive LMS filtering, adaptive RLS filtering, Savitzky-Golay filtering or discrete wavelet transform (universal and local thresholds) [27].

Photoplethysmography (PPG) is optical technique used to estimate the skin blood flow using infrared light. This is non-invasive technique that measures relative blood volume changes in the blood vessels close to the skin. The changes in blood flow can be detected by PPG sensors as changes in the intensity of light, because the light is more absorbed by blood than the other surrounding tissues. PPG signal is typically obtained from the finger. The PPG finger sensor contains a light emitting diode (LED) and a photodetector (PD) which are usually set on the opposite side of the finger. The light is emitted from the LED (usually infrared or red light) and a small part of light intensity changes is detected by the PD. These changes may depend on blood vessel wall movement, blood volume, blood flow, as well as the orientation of red blood cells in the underlying tissue [28].

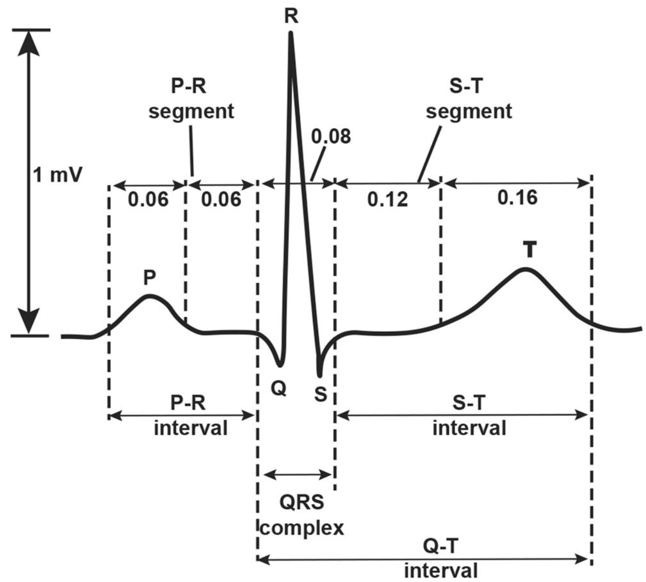

Fig. 1 Typical ECG signal

A PPG signal (Fig. 2) is composed of an AC component and a DC component. AC component is the pulsatile part of the PPG signal and it is obtained when light passes through the arterial blood. This component is strongly related to changes

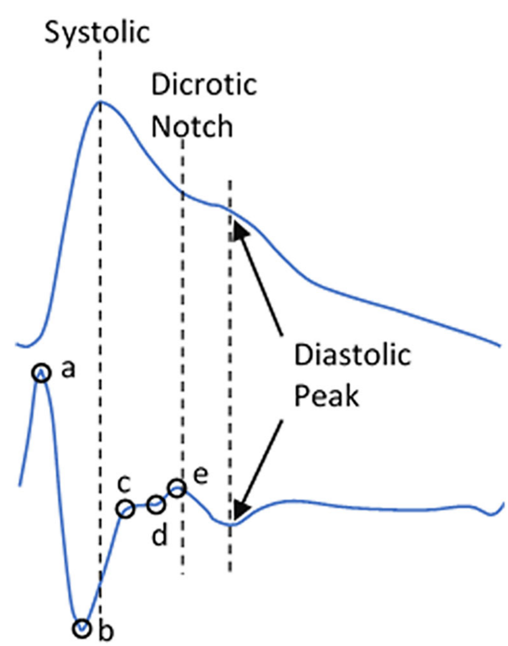

Fig. 2 Typical PPG signal and its Second derivative wave

in the pulsatile pressure and pulsatile blood volume and also is synchronous with the heart rate. The DC component is the non-pulsatile portion, and it is obtained when there is absorption of light by blood in veins, bones and tissues [29]. PPG signal have important information about the blood pressure, respiration, heart rate variability, etc. The time period of each pulse depends on heartbeat, the concentration of various constituent parts of arterial blood and path length of light travelling through the arteries [29–32].

ECG and PPG signals are closely related and depend on the age of the subject, his day-to-day activities and his health, and can therefore be easily changed, especially PPG signal.

BP estimation from ECG and PPG signals

ECG together with PPG signals are the most common combination for assessing BP in a cuff-less continuous monitoring systems, because they are essential for calculating the Pulse Transit Time (PTT). When the heart beats, it pumps blood to all parts of the body. The speed of heart beating is directly proportional to BP. The time it takes for blood to reach the certain location in the human body is inversely proportional to BP and is called pulse transit time (PTT). The speed of this travel corresponds to the pulse wave velocity (PWV). By continuously measuring PTT, SBP and DBP can be estimated [33–35].

PTT can also be described as the time needed for the arterial pulse pressure wave to propagate through a length of the arterial tree. PTT method has been the most commonly employed technique for cuff-less BP measurement. There are two typical methods used to calculate PTT from ECG and PPG. The first one, uses the time delay between the peak of the R-wave in ECG and the fingertip PPG (Fig. 3) to calculate the PTT [36], while the second one, measure the delay of different PPGs acquired from different parts of the body [37–39].

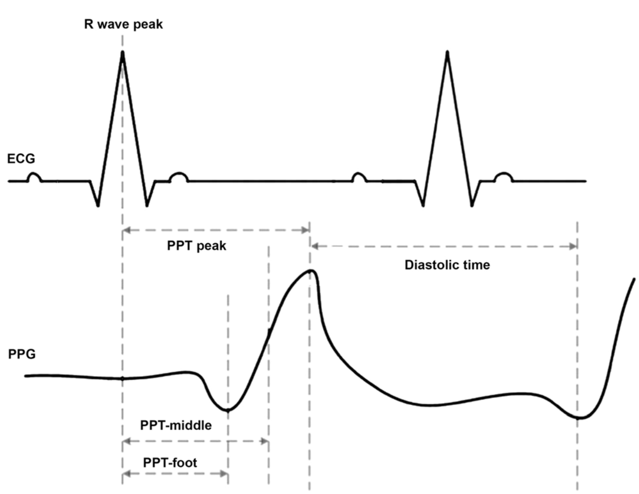

Fig. 3 PTT determined by the ECG and PPG

PTT has shown good correlation especially with SBP. In [40] different models for obtaining systolic blood pressure have been presented and a comparative analysis has been made. These models are based on linear, quadratic and exponential assumptions [41–47], and use different mechanisms and deduction processes, where a, b and c are constants:

1. $SBP = a \ln(PTT) + b$
2. $SBP = a\ PTT^{-1} + b$
3. $SBP = a\ PTT + b$
4. $SBP = a\ PTT^2 + b\ PTT + c$
5. $SBP = a\ PTT^2 + b$
6. $SBP = a\ e^{b\ PTT}$
7. $SBP = a\ PTT^{-2} + b$

The relationship between PTT and BP can be analyzed by using linear [10, 48, 49] or nonlinear regression [50, 51]. Least Square algorithm is a prevalent statistical regression method that has been widely employed in many applications [34, 49, 52, 53]. Alternatively, a kernel regression approach can be used [54]. Many other works tried to fit regression models for BP estimation using PTT [35, 55, 56]. In order to describe more accurately the relationship between PTT and BP various machine learning methods are used [14, 57–60].

Studies have shown that the correlation between BP and PTT is significant, but depends on many parameters, which can vary among different patients [41, 61]. Because of this, some researchers proposed a personalized estimation model, using calibration [10, 62, 63]. According to them, initial and periodical calibration is necessary to obtain acceptable BP estimation. However, for the initial calibration an additional BP monitor as a reference is required. Also, calibration takes time and could be valid for a short time, after which recalibration is required [42].

To overcome this issue, several calibration-free methods were proposed for accurate and reliable estimation of BP. They used support vector machine (SVM) to train and predict BP [64], or a combination of machine learning and signal processing algorithms [65], or artificial neural network with multilayer feed-forward back propagation algorithm [59]. A framework, for continuous and cuff-less estimation of BP, was proposed and evaluated in [55]. Here, PPG and ECG signals are first denoised and after that, their informative features are extracted. These features later serve as an input to a regression model, which calculates the BP value. The evaluation shows that the proposed algorithm works reliably without need for calibration, but for further improvement of the system's accuracy, the authors suggested an optional calibration procedure. Because, not all parameters from PPG and ECG are indicative of BP, in order to automatically trim the redundant parameters a sparse regression-based approach can be used [66]. Comparing with other BP predictive techniques the proposed method yields better results, especially for DBP estimation.

The PTT-based BP calculation may not be sufficiently precise because the regulation of BP in the human body is a complex and multivariate physiological process. Therefore, some additional parameters such as, Heart rate (HR) [40, 52, 67], Pulse wave velocity (PWV) [68, 69], pressure pulse wave (Fig. 4) [48], the photoplethysmogram intensity ratio (PIR) [58], pulse width (PW) (Fig. 5) [70] and Pulse arrival time (PAT) [71, 72] can be used for more accurate BP estimation. Results of these studies have shown that models using an additional parameter are more precise than those who perform BP estimation only from PTT.

Another cuff-less and continuous BP measurement system was developed using a combined PTT and a modified oscillometric method - that eliminates an inflatable pressure cuff [73, 74]. Two sensors placed at the wrist and the index finger were used to estimate BP. This allows patients to move their hand freely, which is one of the benefits of this new promising approach.

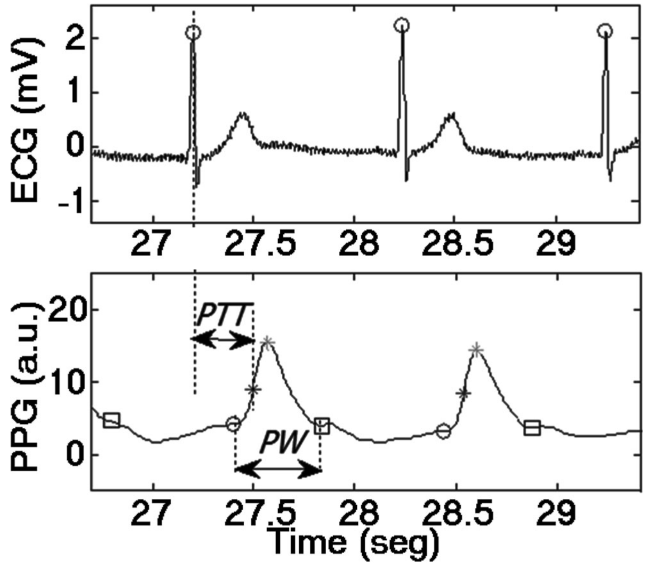

Fig. 5 ECG and PPG signal with PTT and PW representation [70]

BP estimation only from PPG signals

Because PTT can be obtained with PPGs acquired from different parts of the body, estimation of BP only by PPG is possible. PPG is a simple, low-cost and portable optical tecnique that can be used in detecting blood volume changes in tissue. This technique can be used for developing a portable real-time unobtrusive systems capable of continuously monitoring patients for a long period of time in static and dynamic conditions. It has been proven that the meaningful PTT information can be extracted from non-invasive, continuous forms of pulse wave measurements via PPG. The reflective sensor should be placed either on a top of the radial or ulnar artery in close proximity to the wrist, depending on the emerging signal quality. The finger clip can be positioned on any finger. PPG signals obtained on this manner, can be further processed by continuous wavelet transform (CWT), where CWT is used with a fixed range of scales [75]. Finger photoplethysmography together with ballistocardiography (BCG) can also be used for estimation of BP variability for a particular subject [76]. The study has shown that BCG can be a valid and unobtrusive alternative of ECG.

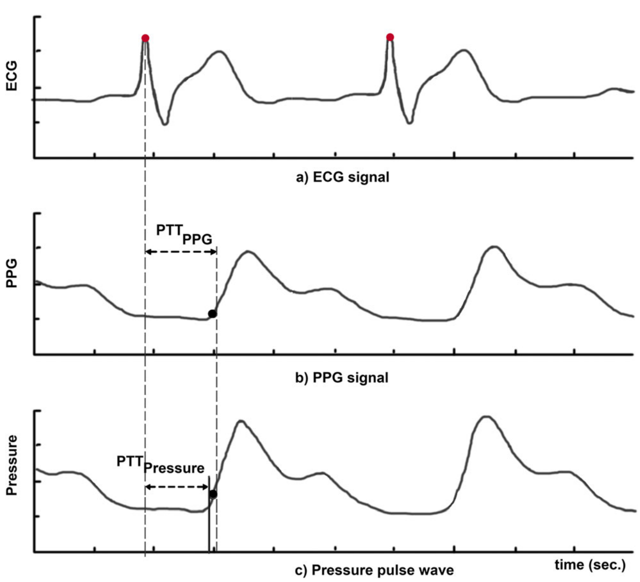

Fig. 4 Principle of pulse transit time calculation [48]

Some studies are proposing multi-site PPG measurements for obtaining PTT. But, taking measurements on obtrusive locations, such as toes or finger, may restrict movement. Also these parts of the body are usually covered by clothing. Therefore, these kind of measurement should be avoided. For these reasons, in [77], authors proposed a system where measurements from the facial arteries are used. The system is integrated into a pair of glasses, and aimed to be used in everyday life. The results of the evaluation show that the device can be used for continuously and unobtrusively monitor BP on a short term basis.

More and more researchers are biased on the fact that there is a linear correlation between the BP and duration of heart beat that can be computed from the PPG signal. But, experimental studies and tests made with different signals have shown that this correlation not always have to be linear. Because of this, machine learning techniques have been applied in some studies [78–80]. In [78] two machine learning algorithms: incremental gradient descent and Neural Network were evaluated. The results have shown that Neural Network outperforms linear incremental gradient descent, so the method should be considered for future studies. Neural networks were also used in [79]. The proposed model takes raw PPG signal as feature and then, employs deep learning technique. But, this model is computationally intensive, and it is difficult to interpret useful physiological information from PPG waveforms. Mainly, features for calculation of BP are defined in one domain and that usually is the time domain. Therefore, in [80] 21 features, based on time and amplitude scale, were selected and used in time-domain of the PPG waveforms. For estimating BP, Neural Network as machine learning algorithm was used. The experimental results have shown that the method can give better results, in estimating BP, than linear regression methods.

Because, the alignment of the collected data and the number of sensors used are the major obstacles for BP estimation when using more than one physiological parameter, BP estimation from single PPG is proposed in some studies, as a possible solution. But, these methods are usually based on correlation between BP and feature vectors. The main problem of these algorithms is their robust performance. Input signals, obtained by sensors, define the performance of feature vectors, so if there is a noise in the input signal, the future vector's quality will decrease, reducing the estimated precision of the BP. In order to find a solution for this problem a new wavelet neural network algorithm for obtaining BP is proposed in [39], where a complete PPG signals are selected as feature vectors. The strength of a hidden layer node utility is improved by fully usage of the low-pass characteristic of Daubechies wavelet. By decreasing the number of multiplication operations and optimizing neural network structure, the computational complexity is quite simplified, that makes implementation and application much easier.

In some cases, the secondary peak of the PPG signal is not always visible. This can lead to the peak shifting of the main peak of the PPG signal, which can influence the precision of the PTT value. This is an essential issue when BP is obtained from PTT. Therefore, it is important to find methods for secondary peak detection. In [81], three types of methods based on linear regression, quadric regression, and cubic regression are proposed, to obtain the relationship between PTT and BP are proposed. The results verify that the proposed detection methods improve the correlation relationship between the adjusted PTT and BP.

Second derivative of PPG (SDPPG) keeps information about aortic compliance and stiffness, which is related to BP. Therefore, in [82], 14 new SDPPG based features combined with conventional 21 time-scale PPG, are presented. Support Vector Regression (SVR), as extension for Support Vector Machine (SVM), is used to minimize the problem with over-fitting.

BP estimation only from ECG signals

Noninvasive BP measurement is also possible using only ECG signal [83, 84]. This method is generally based on the detection of HR, which can be estimated by dividing the RR interval from ECG signal into 60 (Fig. 6). This number is marked as BPM (Beats per Minute).

Due to the fact that HR is directly proportional to the cardiac output, the increase in HR will increase BP, and vice versa, the decrease of HR will also decrease BP [83]. Although the regression model based on HR gives acceptable results, according to this study, more research is needed to make it more accurate.

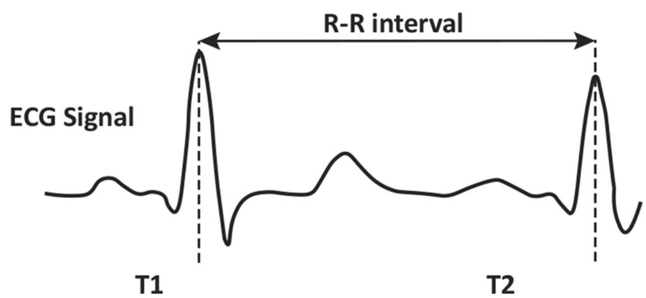

Fig. 6 An illustration of the definition of HR [83]

Other studies were also undertaken to find the relationship between ECG and BP. In [85] a nonlinear analysis was carried out in order to predict an unknown part of one signal from the other. The importance of these results is that they reveal how the relationship between BP and ECG varies from person to person. But, additional research is necessary to predict how ECG affects BP, based on somebody's physical activities and emotional state. In [86], a wavelet transform is used to select T and R waves from ECG and then to perform segmentation on the signal, in order to extract systole and diastole portions from the original signal. In this research, neural networks were applied for obtaining SBP and DBP. An intelligent neural network algorithm for calculating BP in real time, was also used in [24]. It contains multilayer perceptron (MLP) and error back propagation (EBP) that can trace HR variations, when user change his behavior. This approach can be used when BP dynamically changes in order to provide method for continuously BP monitoring even in stressful situations. Another method for BP estimation from ECG is proposed in [86]. This method uses algorithms that offer two distinct methods of BP calculation. First one is based on amplitude modulation of oscillometric pulses and the second is based on temporal modulation of oscillometric pulses.

Outside of these categories in [87] authors described a new method for PTT estimation without ECG and PPG named Eulerian video magnification (EVM) technique. PTT here is simply calculated from the video recorded by the web camera. The experimental results have shown that the PPT measured by the Eulerian video magnification framework is highly correlated with the PTT detected by real pulse sensor.

Devices and systems for continuous BP measurement in AAL applications

For some medical conditions, it is necessary to monitor patient's physiological parameters continuously or on request, while performing their everyday routines. BP is one of the vital parameters that must be constantly monitored in order to prevent health issues. The number of devices and systems designed for continuous monitoring of BP is rapidly increasing in the last decade. These systems include sensor and mobile technologies, wearable and embedded systems, ambient intelligence, etc. and can monitor patients in their homes and residencies during their ordinary activities without intruding the comfort of their everyday life [16, 88].

Ambient Assisted Living Systems (AALS) aims to create an ICT-augmented living environment for supporting independent living for people experiencing some difficulties in day-to-day living as well as enhancing their well-being. They consist of various sensors (medical and environmental), wireless networks, hardware and software applications that are interconnected to exchange data and provide services in AAL environments. The data obtained from these sensors are fused together in order to: control the living environment (for safety and comfort of the patient), provide information about current state of the patient and inform his family, friends or caregivers if some unusual situation happens, and provide information to care and health management.

AALS are usually used for health-care monitoring of elderly, but since their working principles are similar to the principles in smart or intelligent homes, they can be applied in any home [94].

Various AALS have been developed to address specific needs of people. In [89] the authors summarized most of the activities that need to be supported in AAL environment. Monitoring of human vital signs (such as BP) is one of the groups toward which the development of AALS is directed. There are various systems and measuring that are used for this purpose.

In this paper we propose the following classification for continuous BP measuring systems:

- Systems for measuring BP based on smartphone
- Wearable sensor-based systems for BP measuring
- System of sensors and smartphone application.

Systems for measuring BP based on smartphone

Smartphones, equipped with built-in sensors and supported by high speed data transfer services, can become a powerful health-care tool for monitoring patient health. Guided by the fact that smartphones with two microcameras are commonly used nowadays, an efficient method for estimation of PTT based on photoplethysmographic imaging (PPGi) was introduced in [90]. PPGi signals were captured from two microcameras: one placed on an artery at the temple and another on the finger. Therefore, the system measures PPG at two locations, and then, it computes the PTT. High-resolution cameras were also used in [87] for daily health-care monitoring. Eulerian color magnification framework as a method was used to estimate PTT through which the BP was calculated. In [91] the authors extended the oscillometric principle, and developed a cuff-less BP monitoring device that utilize a smartphone. The user provides external pressure on an artery in the finger by pressing an optical sensor overlaying a force transducer on the back of a modified smartphone. A smartphone application provides visual feedback to the patient.

A smartphone application that work together with built-in camera and microphone, is also described in [14]. This type of application can be used as a successful replacement of traditional stethoscope and cuff-based techniques for measuring vital signs like HR and BP. Two different techniques are presented in this article. First one uses two smart phones while the second one uses one phone and a customized external microphone. BP is calculated from the recorded data by computing the pulse pressure and the stroke volume.

Nowadays, smartphones are common gadgets, so these methods for BP measuring can be considered appropriate and convenient. However, user interaction is still needed during the measurement, which can interfere with their regular activities.

Wearable sensor-based systems for BP measuring

Wearable systems for monitoring vital parameters may comprise various types of sensors that can be easily integrated into clothes, textile fiber, elastic bands or can be attached directly to the human body. In recent years, efforts have been made to develop appropriate sensors that are portable, light and low cost. These sensors should be capable to measure various biosignals such as: ECG, electromyogram (EMG), electrodermal activity (EDA), HR, respiration rate (RR), body temperature, arterial oxygen saturation (SpO2) and BP. Systems that integrates these types of sensors should be easy-to-use and should have compact size, low power consumption, and integrated communication modules, in order to communicate with systems' central node, or other systems [92, 93].

The diversity of applicable field of health monitoring systems, corresponds with various system architectures and designs. In [23] a wrist watch-based system for measuring ECG and PPG is presented. From these two signals PTT is obtained, and then BP is estimated from this PTT. In order to achieve a high wearability, a fully ear-worn long-term BP and HR monitor is proposed in [94]. As suggested in this paper, an ECG and PPG sensors can be placed behind the ears in order to acquire a weak ear-ECG/PPG signals, which are further used for BP estimation. Another wearable solution is introduced in [77]. Glabella is a glass prototype that incorporates optical sensors for continuously measure pulse waves at three different sites of users' face. It also includes processing, storage, and communication components, all integrated into the glass frame. One of the advantages of this device is that it doesn't require an interaction with the user.

As previously mention, sensors can be embedded into textiles for unobtrusive and comfortable health monitoring. Therefore, in [84] an ECG sensor and a main board, for processing and transmitting the signal, were mounted on a T-shirt. Processed ECG signal is sent from main board to a PC using wireless module. This signal can be further used for BP estimation. The system gives good quality of the measured signal, which makes it suitable for long-term ubiquitous ECG and BP monitoring.

System of sensors and smartphone application

The emergence of wireless technology, smartphones and wearable sensors are extending the capabilities of monitoring person's physiological signals during daily activities. Body sensor network (BSN) is a wireless network consist of various types of medical sensor and a mobile base unit (a smartphone, tablet or PDA). Each wearable sensor is attach on different parts of human body (depending on the measured parameter). The data obtained from these sensors is transmitted to the mobile base unit which is responsible for data processing and communication with other devices or remote servers. If emergency is detected, the medical staff will be informed immediately, so they can intervene on time. The system can also allow users biofeedback as an early warning.

BSN systems have created new opportunities in health-care allowing monitoring of clinically important parameters (like BP) in non-clinical settings. One such system that incorporate smartphone, HR belt and wristband, is proposed in [52]. The wristband that collect the PPG signals is used as a wrist accessory, and the HR belt that collect ECG signals is placed on the chest. These sensors are used for continuously collecting ECG and PPG signals, which are used for calculating PTT. The sensor data are transmitted via Bluetooth to a smartphone, where all the processing is done. The result of user's BP (calculated from the PTT) is displayed on the smartphone or uploaded to a remote server.

An Intelligent Mobile Health Monitoring System (IMHMS), which can provide medical feedback through mobile device based on biomedical and environmental data is presented in [95]. Various sensors are used for collecting data about temperature, blood pressure, glucose etc. The patient's health status is intelligently predicted based on data analyses, and a feedback is sent to the patient, so that he can actively participate in the health care process.

Similar BSN system, capable of monitoring BP, heart rate, oxygen saturation SpO2, and body temperature is introduced in [96]. The pulse transit time was utilized to estimate BP. The system uses Bluetooth protocol for transferring the data to a mobile device which is connected with remote server through cellular network or WiFi. The Android application, installed on user smartphone, allows the patient to observe his current vital signs, and warn him if unusual situation occurs.

AlarmNet is a wireless sensor network system used for long-term monitoring of patients with different needs [97]. The system has two types of sensors: mobile and emplaced sensors. Mobile sensors are actually wearable sensor devices, worn by the patient. They can measure several parameters like: BP, pulse rate, ECG, SpO2, fall etc. On the other hand, emplaced sensors, can collect information about user location, ambient temperature, light and quality of the air. Sensor data are collected and periodically transmitted to remote stations and back-end database.

Another wearable BSN for continuous cuff-less BP monitoring is presented in [98]. The system utilizes a single lead ECG sensor, placed on the chest, and a PPG sensor placed at the finger or ear. A 3-D acceleration sensor is also used, for obtaining context information - user posture and activity level. Arterial BP is estimated using PAT, and is displayed on a PDA or wristwatch.

More sophisticated system using iPhone application is described in [99]. A novel PPG optical sensor integrated into a standalone device is designed, in order to continuously monitor vital parameters such as: BP, HR, respiration rate, SpO2 etc. Device can function fully independently and can give possibility to the user to read, store, process or transmit data by iPhone application called Sensotrac. The built-in gyroscope and accelerometer in the smartphone, can also be used for calculating number of steps, level of activity, calories burned etc. Sensotrac application can visualize collected data, store it in a database or send it to the Cloud. Another utility of this platform is that it allows doctors to observe the patient's vital signs, to see alerts and send push notifications via API on Cloud.

Similar system that uses sensors for collecting ECG and PPG signals and an Android smart-phone application is introduced in [100]. The data obtained from the sensors are send to the smartphone via Bluetooth. Android application process the data, estimates BP using a PTT-BP model, and displays them on the screen, so the user can monitor his health in real-time.

Completely new approach and method for accurate and continuous BP measurement is presented in [101]. The system uses an acceleration sensor implanted on an artery using minimally invasive techniques. Accelerometer measures the reflected wave transit time (RWTT) through which BP is estimated. The sensor system was implanted in an animal, and an evaluation was conducted. The results show high correlation between RWTT and systolic blood pressure. This new approach facilitates the mobility of a patient and is very promising for future AAL applications.

Conclusion

In the past decade, many efforts have been made to find ways for continuously monitor blood pressure and find a suitable device that will be comfortable enough to be used in everyday life. Ubiquitous BP monitoring is expected to improve hypertension detection and control, by providing feedback to the patient and informing the doctors and caregivers about blood pressure changes during the day. This may help the doctor to determine how effective the BP medication is, and also augment the doctor-patient relationship.

This paper review the current methodologies, devices and systems for continuous cuff-less BP monitoring. According to the reviewed methodologies, the use of ECG and PPG signals is the most common way of estimating BP using regressive methods or in recent studies, including artificial neural networks. But for obtaining these signals, multiple sensors are needed. The advancements of on-chip systems that integrate powerful graphic processing units, offer possibilities for real-time signal processing and execution of complex algorithms. This can boost the research for continuous and accurate BP estimation directly from ECG signals. The application of deep learning algorithms, in this context, can also be considered a promising approach. Regarding the systems used for continuous BP measurement, we concluded that the integration of biomedical body sensors and smartphones, is the most appropriate solution for AAL applications.

However, despite significant progress within the monitoring device industry, the widespread integration of this technology into medical practice remains limited.

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