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Smart-Phone Based Blood-Pressure Devices: A Review

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***Abstract*—Hypertension is a dangerous condition, but simple to diagnose by measuring the blood pressure. Smart-phones are ubiquitous, so a blood pressure device comprising only the smart-phone can make diagnosis commonly available without the need to procure access to a special blood pressure device. This paper reviews recent advances in blood-pressure measurements, specifically with focus on those implemented for smart-phones. Finally, future possible directions are mentioned.**

***Keywords*—smart phone, blood pressure, medical device, sensor**

INTRODUCTION

Hypertension is a dangerous condition, which can lead to cardiovascular disceases, most commonly known is stroke in the heart. In 1990, India saw 1.3 million deaths from stroke, directly related to hypertension, and research suggests this number will only increase in the coming years [1]. Diagnosing hypertension in the population is the first and most important step in order to decrease the risk of hypertension-related diseases. To diagnose hypertension is relatively simple, as it requires primarily knowledge of a person's blood pressure (see Tab. I), thus depends on the availability of a device to measure the blood pressure.

Blood pressure category	Systolic (mmHg)		Diastolic (mmHg)
Normal	< 120	and	< 80
Prehypertension	120 139	or	80 89
High Blood Pressure (Hypertension) Stage 1	140 159	or	90 99
High Blood Pressure (Hypertension) Stage 2	> 160	or	> 100
Hypertensive Crisis	> 180	or	> 110

TABLE I: Blood pressure categories. Source: American Heart Association

Blood pressure is typically recorded as two numbers, written as a ratio like this: Systolic/Diastolic.

The top number (systolic), which is also the higher of the two numbers, measures the pressure in the arteries when the heart beats (when the heart muscle contracts). The bottom number (diastolic), which is also the lower of the two numbers, measures the pressure in the arteries between heartbeats (when the heart muscle is resting between beats and refilling with blood).

Common blood pressure methods are: 1) the auscultatory method used in a clinical setting where a stethoscope and a sphygmomanometer are used to pressurize the upper arm, and

(a) Bluetooth enabled ECG sensor. Source: Clockwise.de (b) Microphone-based digital stethoscope. Source: [7]

Fig. 1: External sensor examples.

listen for blood flow (so-called Korotkoff sounds); 2) the oscillometric method, typically used in-home, follows same principle, but uses electronic analysis of the blood flow instead of human listening.

Both the common methods are cuff-based, meaning they require inflation and pressure applied. This is often disturbing the patient, leading to an overestimation of blood pressure. Thus, cuff-less methods are sought for ease and possibility of continous monitoring.

Measurement of blood pressure has long been an active field of research. Recently methods have been developed with focus on digital sensors, signal processing and machine learning. The remainder of the paper is organized as follows: Section II discus which sensors are used together with their respective signal processing methods. Section III discus the methods used for producing BP output from available sensor inputs. Finally, in Section IV, future improvements are mentioned, and the paper is concluded.

II. SENSORS AND SIGNAL PROCESSING

Observing the patient requires input, either specified by the patient herself, or by the use of sensors. Traditional sensors such as ECG and digital stethoscope (see Fig. 1) have been used together with smart-phones for measuring BP [2]–[6].

For the smart-phone based BP device, several sensors have been proposed, which are available in most of today's smart-phones:

Accelerometer, senses movement of the phone.
Microphone, audio sensor.
Touch-screen, senses finger-movement and finger-pressure on the screen. Camera, visual sensor.

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(a) PPG sensor. The camera records the oxidation of the fingertip. The LED illuminates the fingertip in order to produce a better signal. (b) Microphone sensor. The microphone is positioned near the heart for better signal.

Fig. 2: Smart-phone sensors

1) Accelerometer as heart-beat sensor: The accelerometer provides the smart-phone with knowledge about motion, such as acceleration forces or rotation. In [8], the accelerometer was demonstrated to be able to measure the heart-beat at the heart, by strapping an iPhone to the patient's chest. The accelerometer provides information about acceleration along X, Y and Z axis, and depending on the position of the patient, the heart-beat must be detected along the correct axis, or, possibly a combination thereof. [8] showed that the accuracy of detecting heart-beat was in [0:76; 0:98] when the patient was not moving. When moving (e.g. walking) the signal noise from stepping overshadowed the heart-beat.

2) Camera as photoplethysmography sensor: The camera sensor can be used as a photoplethysmography (PPG) sensor. PPG is sensing change in the oxidation of a body-part, as an effect of the pulse wave. PPG with the smart-phone is based on the flash LED and the camera. The LED illuminates the fingertip, providing a clearer view of the oxidation, and the camera as sensor, see Fig. 2. The change in illumination in the camera is the signal $S_P(t)$, as shown below:

$$S_P(t) = \sum_{i=1}^{h} \sum_{j=1}^{w} \mathrm{green}(I_{ij}(t))| \qquad (1)$$

where the resolution of the captured image is h w, $I_{ij}(t)$ is the pixel i; j in the camera image at t and green is a function to extract the green color intensity from the pixel.

PPG is a very commonly used sensor [3]–[5], [9]–[13] due to its robustness towards interfere from other sensors, however, smart-phones usually contains only one such sensor (LED is not available for front camera).

3) Touch screen as a strain sensor: The touch screen in smart-phones is commonly used as a navigational tool, by to measuring the position of the finger on the screen. However, they also allow to measure variation in pressure. This has been used in Fig. 5(b) where the finger is placed on top of the screen. When the pulse wave reaches the finger, it gives a slight change in pressure, which is the output signal of this sensor.

4) Microphone as un-amplified stethoscope: The microphone in the smart-phone can be used as a stethoscope. As with a normal stethoscope, the faint heart sounds are amplified. As

the microphone is prone to outside noise, this requires silence and signal filtering to extract the heart sound. Fig. 5(a) uses the microphone to measure pulse wave at the heart.

A. Processing sensor signals

Sensor signals are typically noisy. For example, an audio-waveform from a microphone encodes several frequencies from surrounding noise, and a plethysmographic sensor gives a subtlely different illumination for each frame, because of changed light conditions in the room of the patient.

The methods for measuring blood pressure need to know the pulse-wave, and processing the raw signal is done in order to get a smooth curve, where the pulse-wave can be confidently detected.

1) Band-pass filtering: Band-pass filtering is a combination of a low-pass filter and a high-pass filter. The low-pass filter allow wavesforms in the signal with a frequency below a specified threshold to be passed through without modification, while higher frequencies will be removed by filtering them out. A high-pass filter does the opposite, except allowing high frequencies to pass.

Depending on the application, typically band-pass filtering is used over audio or ECG waveforms where the interesting frequencies in the signal are known, and unwanted frequencies are likely to appear.

2) Smoothing: The purpose of smoothing is to minimize the effect of noise in the signal. Two types of smoothing are commonly used. Moving-average smoothing S'_M assigns the signal value to the average of a window of input signal values, defined as:

$$S'_M(t) = (w_1 S(t) + w_2 S(t\ 1) + ::: + w_n S(t\ (n\ 1)))\ ;\ w = (1/n \ldots 1/n) \qquad (2)$$

where S(t) is the input signal, and n is the window-size.

Exponential smoothing is another popular smoothing function, which is defined recursively as:

$$S^0_E(t) = S(t) + (1 \quad)S^0_E(t \quad 1);\ S^0_E(0) = S(0) \qquad (3)$$

again S(t) is the input signal and is the smoothing factor. Fig. 3 exemplifies the use of smoothing in an ECG signal.

3) Peak detection: Peak detection algorithms are deployed for analysis of the filtered and smoothed signal, to find the timing of the pulse-wave. Peak algorithms is a large topic and outside the scope here, however a commonly threshold based method is given [14].

The threshold method is based on the observation that between each peak, there must be a trough. Given a threshold each peak and trough can be defined as:

$$^{X}P_j\ ^{X}T_i\ ^{+X}P_j \setminus {}^{X}T_{j+1}\ ^{+}\ \ ^{X}P_j \qquad (4)$$

$$^{X}T_i\ ^{X}P_j\ ^{X}T_j\ ^{\setminus X}P_{j+1}\ \ ^{X}T_i \qquad (5)$$

where X_{Pj} is the j^{th} peak in X and X_{Ti} is the i^{th} trough. Noise in the signal below the threshold does not trigger another peak or trough, and the definition ensures that a trough always follows a peak, and vice versa.

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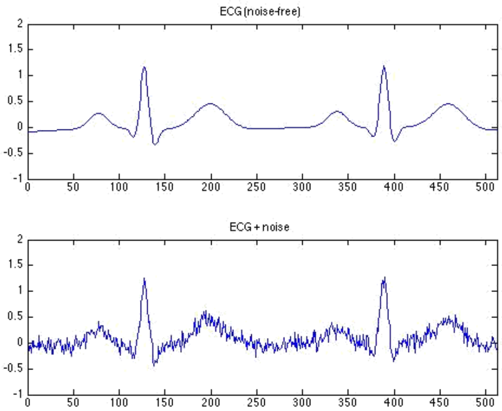


Fig. 3: Prototype ECG signal noise removed by exponential smoothing

III. METHODS

A method describes how input from sensors can be used to calculate the output BP. The methods found in literature are based on PWTT, machine learning, or hybrids thereof. In the following the PWTT method is described and variations in literature given, after which the machine learning and hybrid methods found are mentioned.

A. Pulse wave transit time

Blood pressure is measured as systolic blood pressure and diastolic blood pressure, and the pulse wave transit time (PWTT) method is a relatively new method thereof, which has now been validated quite well in the medical community [13], [15].

When the heart pumps it triggers a pulse wave which travels from the heart along the arterial tree. One of the parameters that decides the velocity of the pulse wave, is the arterial stiffness, i.e. the blood pressure. A shorter pulse wave transit time means a higher blood pressure. In order to measure PWTT the timing of the pulse wave must be measured at two points, one at the origin of the wave (the heart) and one away from the origin (typically the fingertip). An example is shown in Fig. 4, where ECG and photoplethysmography is used as pulse wave signals.

Several methods exists for estimating blood pressure from the measured PWTT f : PWTT ! P . A relatively complete method was given by [3], which requires only few other parameters than the PWTT. Their method is outlined below.

1) Systolic blood pressure: The change in systolic blood pressure has a linear relationship with the change in the pulse transit:

$$P_S = \;\; 0{:}425 PWTT \quad (6)$$

By integration and experimental regression they found the following relation:

$$P_S = \;\; 0{:}425 \;\; PWTT + 214 \quad (7)$$

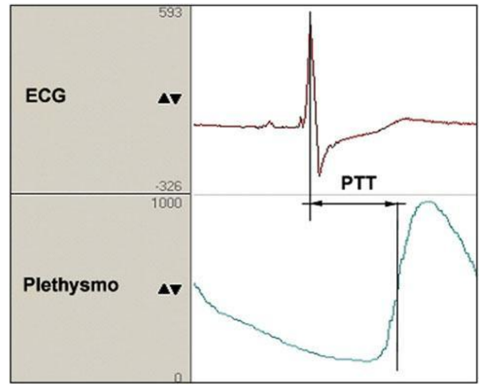


Fig. 4: Example PWTT measured as onset of pulse wave in the ECG signal at heart, and the photoplethysmography signal at fingertip. Source: [15]

2) Diastolic blood pressure: To estimate the diastolic blood pressure, the following relation between systolic blood pressure, diastolic blood pressure P_D and pulse pressure P_P is used:

$$P_D = P_S \;\; P_P \quad (8)$$

The pulse pressure can be calculated from knowing the heart rate HR (or, pulse rate) number of beats per minute as reported by the number of peaks per minute from either of the used sensors as follows:

$$BSA = 0{:}007184\ Weight^{0:425}\ Height^{0:725} \quad (9)$$

$$SV = \;\; 6{:}6 + 0{:}25(ET \;\; 25) \;\; 0{:}62HR + 40{:}4BSA \;\; 0{:}51Age \quad (10)$$

$$P_P = \frac{SV}{(0{:}013W_t \;\; 0{:}007Age \;\; 0{:}004HR) + 1{:}307} \quad (11)$$

where ET is the time between first and second heart sound, Height, Weight and Age are features of the patient and W_t is the window size used in calculating HR.

While [3]'s given method is very complete, similar works [4], [15] agree on the linear relationsip between PWTT and P_S, but offer different methods of estimating actual parameters. [10] does not estimate at all but simply assigns constants empirically, arguing that for practical uses it is good enough.

B. Machine learning methods

Machine learning methods have also been applied. Machine learning by nature does not measure BP, but predicts it. Machine learning in this context is a process in which a model is learned from examples, rather than defining the model in details. f : PWTT ! P is the model that should be learned.

Given a set of examples D and a hypothesis space H:

$$D = f(x_1; y_1); (x_2; y_2); :::; (x_n; y_n)g \;\; (X \;\; Y)^n \quad (12)$$

$$H \;\; fh : X ! Yg \quad (13)$$

where each example (x; y) belongs to their respective domains X and Y, the learning algorithm selects an optimal hypothesis f ,

$$f \;\; 2 \arg \min_{h2H} \;\; {}^Z_{X\,Y} \, l(h(x); y) \;\; L(\;\; ; \;\;) \;\; X \;\; Y \quad (14)$$

Feature group	Features	Uses
Patient body features	Age, weight, height	[9], [18]
	Body mass index, waist, hip	[17]
Patient environmental features	Smoking habits	[18]
Pulse wave features	Position and amplitude of onset, Systolic Peak, Point of Inflection, Dicrotic wave, sys-tolic diastolic time difference	[9], [18]

TABLE II: Features used in machine learning based BP prediction.

where l is a loss-function and L is an unknown data generating process representing the actual learning algorithm. The output function f will, given an unseen example predict the BP.

Examples of learning algorithms are: ANN (artificial neural network), SVM (support vector machine) and BayesNet (Bayesian Network). As their working is a huge topic, please refer to [16] for further details.

Several ways of predicting are given:

Binary classification [11], [17]: Predict whether the patient has high blood pressure or not, i.e. f : PWTT ! P; P 2 f0; 1g

Multi-class classification [11]: Predict which hypertension group the patient is in, see e.g. Tab. I, for which P 2 f0; 1; 2; 3; 4g.

Regression [9]: Predict the values for P_S and P_D of the patient, i.e. P 2 R

In the PWTT method, the PWTT itself is required, along with several contextual attributes of the patient. In a machine learning setting these are called features. Tab. ?? gives an overview of the features proposed in existing methods.

C. Alternative methods

Several hybrids and alternative methods have been proposed, which may be interesting for future smart-phone based BP devices. Some work has been focused on new sensors directly measuring the BP: [19] present a sensor, which uses a specially designed strain sensor to measure BP. The sensor is small and cuff-less meaning it would fit in a smart-phone design. Likewise, [20] proposed an extended PWTT method based on an ICG sensor to measure volume more precisely at the heart, together with PPG at the fingertip. Their ICG sensor is bluetooth enabled and can be used with smart-phones.

Without additional sensors, [10] has proposed a PWTT method which used only the pulse wave at the fingertip to estimate PWTT by considering peaks in the twice-differentiated pulse wave and a learning phase where PWTT is measured at heart-height and one arm-length below heart-height, by moving the finger up and down.

IV. DISCUSSION AND CONCLUSIONS

In this section the accuracy of current methods is evaluated, based on which future directions are discussed, and the paper is concluded.

A. Accuracy

The new BP measurement devices show promising reported accuracy in measuring values consistent with traditional BP measurement (such as a sphygmomanometer or a cuff-based oscillatory device). For the methods mentioned in this paper, the accuracy has been collected into the overview shown in Tab. III.

Method	Sensors	Reported accuracy
Pulse wave transit time (PWTT)	PPG and Microphone [21]	0:9
	PPG and digital stetho-scope [3]	[0:94; 1:0]
	2 x PPG [3]	[0:94; 0:99]
	PPG and ECG [20]	[0:91; 0:98]
Differentiated PWTT [10]	PPG	[0:83; 0:92]
Pulse wave	PPG [11], [18]	[0:88; 0:97]
Pulse wave and patient features	PPG [9]	[0:75; 0:95]
Patient features [17]	(Nil)	[0:72; 0:85]

TABLE III: Overview: Reported accuracies for discussed methods and sensors. Accuracy means correlation with tra-ditional BP measurement.

The accuracy for all methods is within [0:72; 1:0]. The most accurate methods are based on external sensors [3], [20], but alternative methods considering only a single PPG sensor along with contextual features are also showing good accuracy [9], [11] under ideal conditions.

B. Future work

While the reported accuracies are already quite good, there is still room for improvement under less-than-ideal conditions. Adding more sensors allows to measure the heart-beat and finger pulse more precisely. In the smart-phone based device it is however not always a solution, as the sensor's signals may overlap.

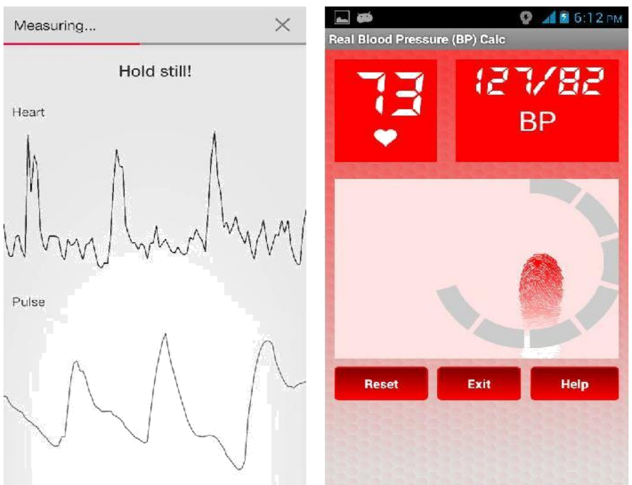
C. Human computer/device interface

All blood pressure devices display only the same three outputs: 1) pulse; 2) diastolic pressure; 3) systolic pressure (see two example Android based applications in Fig. 5). For the health-care professional, this information is essential and based on the training, a proper diagnosis can be made. For the patient the story may be different, remembering the limits for a normal condition, or, when a visit to the doctor is imminent, may not be possible.

Another interesting direction in human computer/device interaction is that some methods may offer continuous measurement of BP. This could give room for research into methods of alerting the patient (or doctor), should a given BP event occur.

D. Blood pressure variability

It has been shown that the blood pressure is not static, but rather continuous [22]. While standard deviation of the accuracy is not mentioned here (lack of data in the referred papers), methods with a wide interval suggests unstable performance, possibly based on other factors, as suggested by the blood pressure variability.



(a) Source: Instantbloodpressure.com (b) Source: Purepush.org

Fig. 5: Screen-shots from two Android blood-pressure measurement applications.

The use of machine learning methods and environmental sensors (including Internet, such as Facebook or Twitter integration) in this area could be interesting, to give a more precise measurement of blood pressure, considering the variability.

E. Conclusion

In conclusion, this paper has introduced the problem of hypertension, and reviewed current trends in smart-phone based blood-pressure devices to make hypertension monitoring easier. Used input sensors have been described and methods reviewed; found to be of good accuracy to benefit the hyperten-sion community. Finally, possible future directions have been given.

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