Dynamic Threshold Algorithm to Evaluate Trustworthiness of the Estimated Blood Pressure in Oscillometry

Iraj Koohi, Saif Ahmad, Izmail Batkin, Voicu Groza, Shervin Shirmohammadi, and Hilmi R. Dajani

Blood pressure (BP) readings in oscillometry are very sensitive to the posture of the body, arm, and body movements during the BP measurements, so measuring conditions are the first important factors for trusted BP readings. Next is the BP estimation algorithm, which is responsible to convert the cuff deflation curve (CDC) pressure signal to accurate BP readings. With proper measuring conditions and an accurate BP estimation algorithm one can expect trusted BP readings. Trustworthiness of the BP readings is still a challenging issue in automated oscillometric BP monitors, and patients need to see the doctor for trusted measurements. To this end, we have proposed a novel method called a Dynamic Threshold Algorithm (DTA) that evaluates trustworthiness of the BP readings immediately after the BP is estimated, such that the patient can decide whether to repeat the measurement or not. DTA employs the heart rate (HR) of the subject and determines a specific threshold (TR). TR is used to determine maximum and minimum limits for trustable pressures (SBP2, DBP2) of a given subject. The limits are called trusted boundaries (TB). Trusted boundaries are compared with the estimated systolic blood pressure (SBP) and diastolic blood pressure (DBP) to determine trustworthiness of the measured BP. BP readings are trusted if estimated SBP and DBP are inside the TB and untrusted or labeled an outlier if otherwise. In this research, DTA is applied on three different datasets of healthy and sick subjects, outliers are determined and removed from the datasets, and remaining recordings are validated against references and compared with validated results of original datasets. According to observations, improvements were significant after outliers were removed from the datasets.

Introduction

Arterial blood pressure (BP) is an important vital sign that carries significant information about the physiological state of a person [1] (Fig. 1). Systolic blood pressure (SBP) is the maximum blood pressure during heart contraction and ejection of the blood towards peripheral vessels. Diastolic blood pressure (DBP) is the minimum blood pressure exerted upon the wall of arteries while heart relaxes. The average BP over a cardiac cycle is called mean arterial pressure (MAP).

Blood pressure can be measured either invasively or non-invasively. The most accurate method for measuring BP is the invasive method, which is widely used in intensive care units (ICU), in which a catheter is placed inside the artery for direct BP measurement [2]. However, the requirement of highly trained staff and possibility of bleeding are two significant drawbacks. Alternatively, non-invasive methods to measure BP are much safer, easier to use, and do not require high expertise. Non-invasive methods measure BP indirectly using an external cuff and are commonly used in hospitals and home-based monitoring systems (HBMS).

The auscultatory method is considered the gold standard among non-invasive BP measurements. This technique utilizes a stethoscope, sphygmomanometer, and a cuff that is used to occlude and relieve arteries. The systolic and diastolic pressures are determined by a trained examiner listening to the so called Korotkoff sounds. SBP corresponds to the appearance of the first sound after releasing the arterial blood flow, while DBP corresponds to the last sound before silence. The auscultatory method is very sensitive to noise and movements and requires trained examiners [3], [4].

Alternatively, there are automated monitoring devices that employ oscillometry to estimate BP. Oscillometry is the most popular non-invasive technique for automatic estimation of blood pressure as it can be relatively easily implemented in automated BP measurement devices [5]–[7]. The use of automated BP monitoring devices is growing fast since its use does not require much expertise and can be performed by patients

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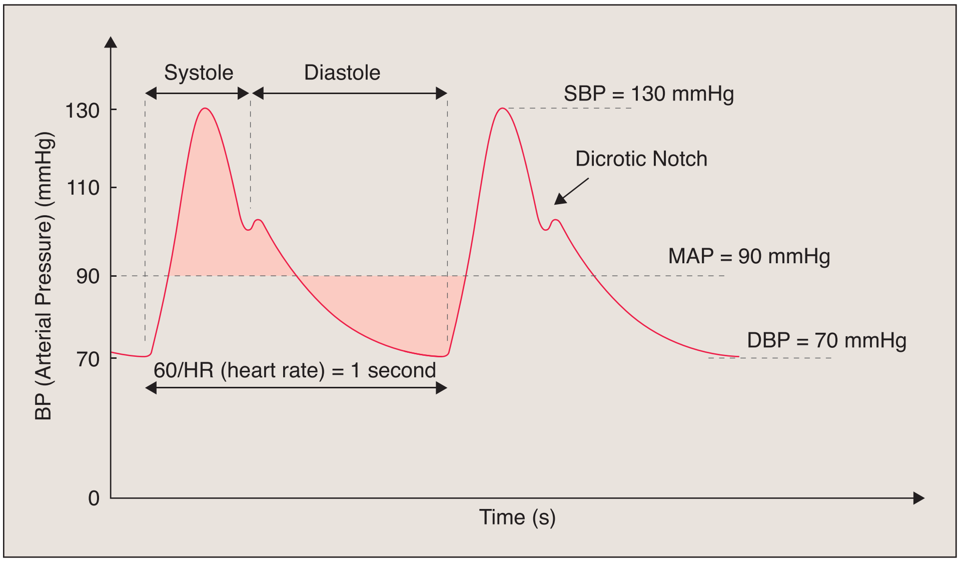

Fig. 1. Blood pressure in large systemic arteries.

at home. Most of the oscillometric algorithms rely on empirical coefficients that are employed to evaluate systolic and diastolic pressures, and since these coefficients may differ among the patients, the accuracy of the BP readings is affected, rendering the technique untrusted. Oscillometric waveform (OMW) is usually the only signal extracted in oscillometry [8] from the pressure in a cuff applied on subject's arm or wrist and analyzed to estimate BP. Blood pressure characteristics vary over time and with emotional and environmental factors [9]. Oscillometry can be performed by patients at home and can operate in noisy environments. In oscillometry, like in the auscultatory method, an inflatable cuff is wrapped around the subject's upper arm or wrist and is inflated to a supra-systolic blood pressure (SSBP). The cuff is then slowly deflated to a sub-diastolic blood pressure (SDBP) while recording the cuff deflation curve (CDC) which is the pressure within the cuff. OMW contains oscillometric pulses that are induced into the cuff by arterial BP pulses over the cuff deflation period. It is extracted from the recorded CDC and is used to estimate BP non-invasively. Several techniques such as filtering and detrending are used to extract OMW from the CDC.

Oscillometric pulses are often corrupted by noise and artifacts caused by body movements, muscle contraction, posture of the body, and arm during the BP measurement [10]. In this research, these elements are used to define measuring condition factors. BP estimation algorithms convert OMW pulses to BP readings. Even with the most accurate estimation algorithm, one cannot get accurate BP readings if it fails to consider proper measurement conditions. Both measuring conditions and accuracy of the BP estimation algorithm are important for trusted BP readings.

Trustworthiness of the BP measurements in oscillometry is the main challenging issue, especially when it comes to patients with cardiovascular diseases such as obesity, atrial fibrillation, and arrhythmia [11]. This limitation determines physicians' lack of trust in the current oscillometric monitoring devices, and this is why patients are required to see their doctor regularly for trusted measurements.

To this end, a Dynamic Threshold Algorithm (DTA) is proposed to determine trustworthiness of the measured BP. A threshold (TR) is found by the algorithm, based on the heart rate of the patient, and is used to locate the oscillometric pulse at MAP ($\text{PULSE}_{\text{MAP}}$) from the OMW. Pressure of the located pulse (MAP2) is estimated from averaging the cuff pressures at starting and ending points of the $\text{PULSE}_{\text{MAP}}$. Peak (pk) and trough (tr) of the $\text{PULSE}_{\text{MAP}}$ are used to determine upper and lower limits (SBP2, DBP2) for trustable SBP and DBP, respectively. These limits are called trusted boundaries (TB). TB are used to evaluate trustworthiness of the estimated BP. The measured BP is considered trusted if both SBP and DBP are inside the TB. Otherwise, it is untrusted, which is considered an outlier in this research. The patients can repeat the measurement until a trusted measurement alarm is observed or see the doctor if repeatedly untrusted measurements occur.

In this research, three different datasets of healthy and sick subjects with cardiovascular diseases are employed to test the DTA. The DTA is applied to the datasets, outliers are determined, and estimated pressures are validated against references and compared before and after removing the outliers from the datasets.

Oscillometric Measurement Methods

Two popular BP estimation algorithms, namely Maximum Amplitude Algorithm (MAA) and Maximum/Minimum Slope Algorithm (MMSA), are employed to estimate BP prior to application of the DTA.

A cuff is wrapped around the subject's upper arm and air is pumped into the cuff bladder until the brachial artery is completely occluded. Cuff pressure at this point is equal to supra-systolic blood pressure (SSBP). Next, the cuff is slowly deflated with a constant deflation rate of approximately 4 mmHg/sec to a minimum pressure equal to the sub-diastolic blood pressure (SDBP). A pressure transducer records the cuff pressure, as shown in Fig. 2. It is generally accepted that the information pertaining to SBP and DBP is embedded on this curve, and that is why CDC is the focus of all oscillometric estimation algorithms [12].

Oscillometric Waveform (OMW) Extraction

CDC is composed of slow-varying component determined by the deflating cuff pressure and pressure pulsations induced by

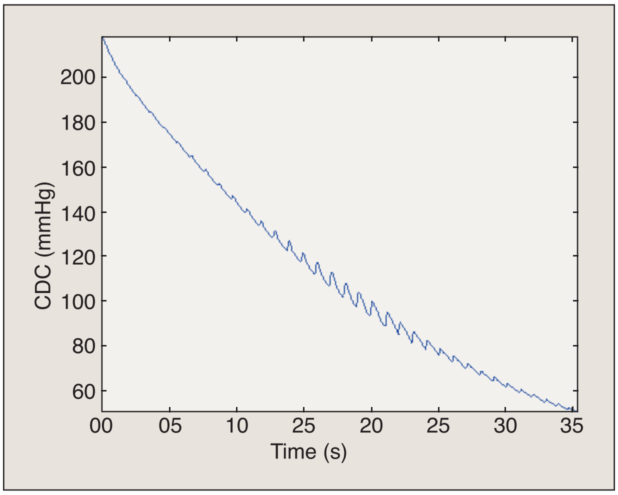

Fig. 2. Sample CDC recorded by a pressure transducer embedded in the cuff system.

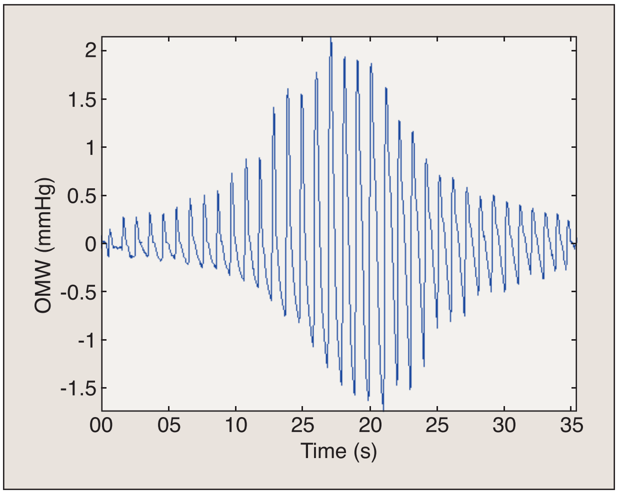

Fig. 3. Sample OMW extracted from the CDC using the detrending approach.

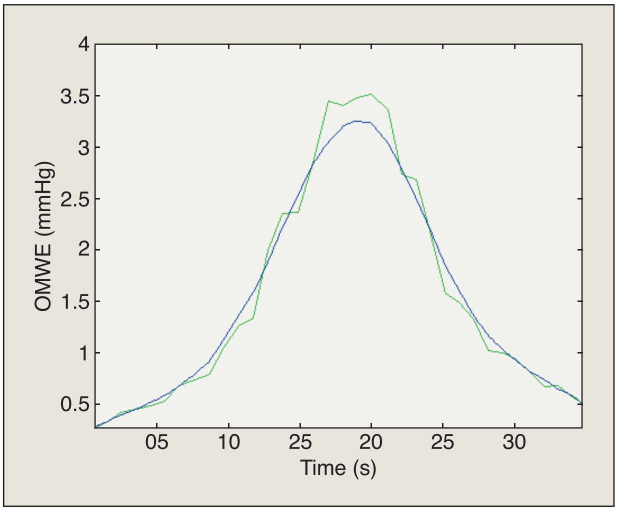

Fig. 4. Obtained OMWE (green) and smoothed OMWE (blue).

the artery known as OMW pulses. The amplitude of the OMW pulses increases to a maximum and then decreases with further cuff deflation. There are two main approaches to extract OMW from CDC, namely filtering [13] and detrending [14] methods.

The filtering method removes the frequency components belonging to the deflating cuff pressure and keeps everything else, including the frequency components of the OMW pulses. It is important to set the lower and upper cutoff frequencies to eliminate only the deflation pressure and keep the oscillating frequency components. Generally, lower cutoff frequency for high-pass or band-pass filters is set between 0.3 and 0.5 Hz, and upper cutoff frequency for band-pass filters is set around 20 Hz to eliminate high frequency noise.

In the detrending method, a curve of best fit that represents the deflating cuff pressure is constructed and subtracted from the recorded CDC. Fitting the line requires locating the beginning of each oscillometric pulse on CDC. Points are then joined together to construct a line corresponding to decreasing CP. A plot of the OMW extracted by the detrending method is shown in Fig. 3.

Oscillometric Waveform Envelope (OMWE) Detection

Oscillometric waveform envelope (OMWE) is formed by subtracting the trough of OMW pulses from corresponding peak pressures. Since the OMWE is usually corrupted by artifacts that generate erroneous peak values, the obtained OMWE is smoothed using a low-pass moving average filter. A sample OMWE is plotted as a function of time in Fig. 4. Both MAA and MMSA algorithms use OMWE to estimate BP.

Maximum Amplitude Algorithm (MAA)

MAA is the most popular estimation algorithm in oscillometry and approximates MAP as CP at a point when the OMWE attains a maximum and then linearly relates SBP and DBP to the MAP using two empirically derived ratios. These ratios serve to determine the time points at which the cuff pressure coincides with the SBP and DBP, respectively [13] (Fig. 5). It has been shown that the MAP may be estimated accurately by MAA [4] while, due to the sensitivity of the method to variations in BP waveform, pulse pressure and arterial compliance, the systolic and diastolic pressures cannot be precisely determined. Moreover, it has been observed that the ratios change as the parameters of the cardiovascular system vary between different health conditions, age, or populations [15]. Therefore, MAA is not reliable for accurate BP measurements, and coefficient-free algorithms are recommended as a solution.

Maximum / Minimum Slope Algorithm (MMSA)

MMSA estimates SBP and DBP from slopes of the OMWE. Drzewiecki has analyzed derivatives of the OMWE against the cuff pressure and found that the first derivative of the OMWE reaches a maximum corresponding to SBP and a minimum that corresponds to DBP [15]. In other words, SBP and DBP are equal to CP at which the first derivative of the OMWE becomes maximum and minimum, respectively (Fig. 6). The MMSA is coefficient-free but still very sensitive to noise such as motion artifacts.

Dynamic Threshold Algorithm (DTA) for Evaluating BP

As stated above, proper measuring conditions and an accurate estimation algorithm are required for trusted BP readings. Otherwise, measurements are untrusted and should be ignored by the examiners. The problem is that, in classic methods, the subjects have no input about the trustworthiness of the measured BP to accept or not the measurement results. The study in [16] suggests that a 3 to 4 mmHg increase in SBP translates into 20% higher stroke mortality and 12% higher mortality from ischemic heart diseases. Therefore, even small errors in estimated BP could have large consequences on health condition of the patients [9], especially when it comes to patients with obesity, arterial stiffness, and atrial fibrillation [8]. To this end, DTA is proposed to evaluate trustworthiness of the measured BP. Therefore, patients will have the option to repeat the measurement if untrusted.

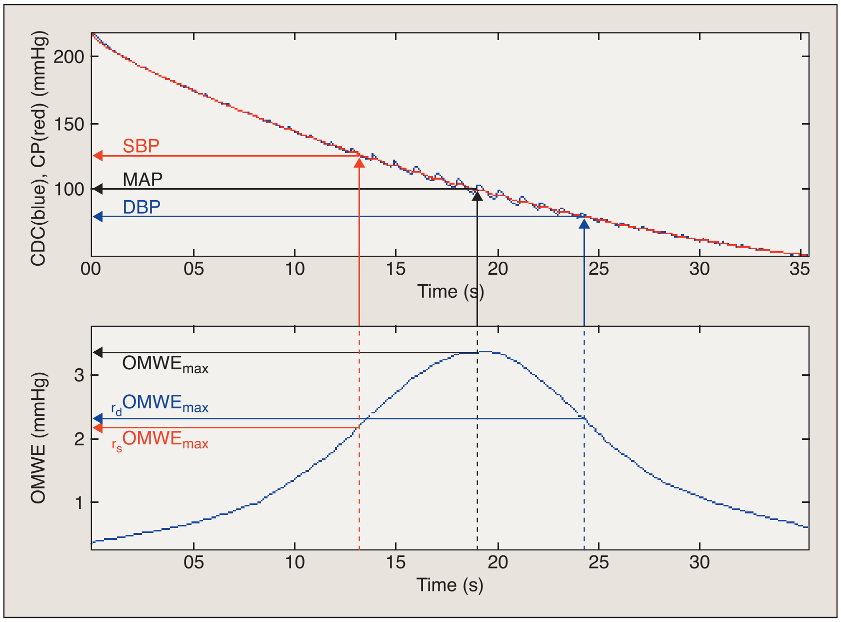

Fig. 5. Procedure of the maximum amplitude algorithm (MAA). Cuff deflation curve (up-blue) is shown as a sample BP recording; cuff pressure (up-red) is extracted using the detrending method. OMWE (down). CP at which the smoothed OMWE attains maximum is determined as MAP. CP at which the amplitude of the OMWE reaches the $r_s.OMWE_{max}$ is determined as SBP. CP at which the amplitude of the OMWE reaches the $r_d.OMWE_{max}$ is determined as DBP.

To apply the DTA and evaluate trustworthiness of the estimated BP, the two popular algorithms of MAA and MMSA are employed to estimate BP. MAA and MMSA estimation algorithms are not the focus of this research but DTA that determines untrusted measurements. To test DTA, estimated SBP and DBP are validated against references and compared with corresponding validated results after removing the outliers from all datasets.

DTA is based on the MAP equation in (1) that approximates MAP from SBP, DBP, and HR of the subject [17]. The MAP equation is defined as a function of HR, because any change in HR will change the time intervals of systolic and diastolic phases at each cardiac cycle, and SBP, DBP, and MAP will change accordingly (Fig. 1).

$$MAP = DBP + \left(0.33 + 0.0012HR\right)\left(SBP - DBP\right) \qquad (1)$$

In [18], the MAP was approximated from SBP and DBP without contribution of the HR. This approximation was used in [19] to determine a fixed threshold that equals 2 and develop our Ratio2 algorithm to evaluate the trustworthiness of the BP readings in oscillometric monitors. According to the observations from our recent research, where the Ratio2 algorithm was tested on more datasets with a broader variety of subjects that included sick patients with cardiovascular diseases, we could not observe the expected improvements in accuracy of the results. Therefore, the fixed threshold was replaced with a dynamic threshold based on HR of the subjects.

The amplitude ratio of OMW pulses are calculated by dividing pk to |tr| of the pulse. A sample $PULSE_{MAP}$ is plotted against pulse number in Fig. 7.

In this research, the amplitude ratio of the $PULSE_{MAP}$ is approximated by TR in (2) and is used to locate $PULSE_{MAP}$ of a given subject.

$$TR = \frac{[1 - (0.33 + 0.0012HR)]}{(0.33 + 0.0012HR)} \qquad (2)$$

TR is equal to 2 if one ignores the contribution of the HR in (2). Moreover, in the previous study, MAP was estimated from MAA and used as a reference to locate $PULSE_{MAP}$, while in this research MAA is not used, and $PULSE_{MAP}$ is located as the pulse with closest amplitude ratio to TR. Especially when it comes to more trials and sick subjects, in some cases we observed a false maximum in OMWE around the reference MAP (MAP_{ref}) that deviated the estimated MAP from its true position, where MAP_{ref} is determined from SBP, DBP, and HR in (1). For example, in Fig. 8, the reference MAP (MAP_{ref}) is 124 mmHg, while the estimated MAP by MAA is 97 mmHg. This false maximum accordingly resulted in a false MAP. The true maximum is where we could get the MAP equal to 120 mmHg, which is much closer to the corresponding reference MAP (MAP_{ref}). According to the observations, we could get closer to the true maximum by employing DTA and locating the $PULSE_{MAP}$, and the true MAP is estimated by DTA as MAP2 accordingly. Peak and trough amplitudes of $PULSE_{MAP}$ have an important role in DTA, so $PULSE_{MAP}$ should be located precisely. In conclusion, MAA has shown not to be always reliable for locating $PULSE_{MAP}$, so the Ratio2 algorithm was extended to DTA from this point of view as well.

$PULSE_{MAP}$ location is found by comparing the amplitude ratio of all oscillometric pulses with threshold TR. $PULSE_{MAP}$ is the pulse with the closest amplitude ratio to TR. Amplitude Ratio of the oscillometric pulses at MAP for one recording is plotted against CP as illustrated in Fig. 9.

DTA is illustrated in Fig. 10. Starting from the OMW extracted from the input CDC recording by utilizing the detrending method, the pressure of the located pulse is the closest pressure to MAP which is estimated by averaging the cuff pressures at starting (CP_s) and ending (CP_e) points of the $PULSE_{MAP}$. The estimated MAP is called MAP2. HR is determined from the number of the oscillometric peaks per minute.

Peak (pk) and trough $|tr|$ of the $PULSE_{MAP}$ are proportional to SBP and DBP with proportional constants χ_s and χ_d, respectively. Therefore, we replaced SBP and DBP in (1) with $\chi_s pk$ and $\chi_d |tr|$ in (4), respectively. Moreover, the two constants are related by the constant k.

$$\chi_s = k\chi_d \tag{3}$$

We tested the DTA for all classes of values of k, i.e., smaller, greater or equal to 1, by detecting and removing the outliers and comparing the mean absolute error (MAE) and standard deviation of errors (STDE) of these validated results against references. The maximum improvement has been observed at k =1 for all datasets.

With $\chi = \chi_s = \chi_d$ and replacing MAP in (1) with MAP2 of (4), we estimated the proportional constant χ in (5). This proportional constant is then used to estimate upper limit (SBP2) and lower limit (DBP2) in (6), (7) for trustable SBP and DBP respectively. The estimated upper and lower limits are defined as trusted boundaries.

$$MAP2 = \chi|tr| + (0.33 + 0.0012HR)(\chi pk - \chi|tr|) \tag{4}$$

$$\chi = \frac{MAP2}{(0.33+0.0012HR)pk + [1-(0.33+0.0012HR)]|tr|} \tag{5}$$

$$SBP2 = \chi pk \tag{6}$$

$$DBP2 = \chi|tr| \tag{7}$$

Due to nonlinear properties of cardiovascular parameters at each heartbeat, such as heartbeat variability, vessel compliance, and the measuring cuff system itself, we need to correct the estimated TB. To apply correction, the absolute distance of R2 from TR is estimated in (8) and applied to previously estimated TB to determine corrected TB in (9), (10).

$$d = |R2 - TR| / TR \tag{8}$$

$$SBP2 = \chi pk + d\chi pk \tag{9}$$

$$DBP2 = \chi|tr| - d\chi|tr| \tag{10}$$

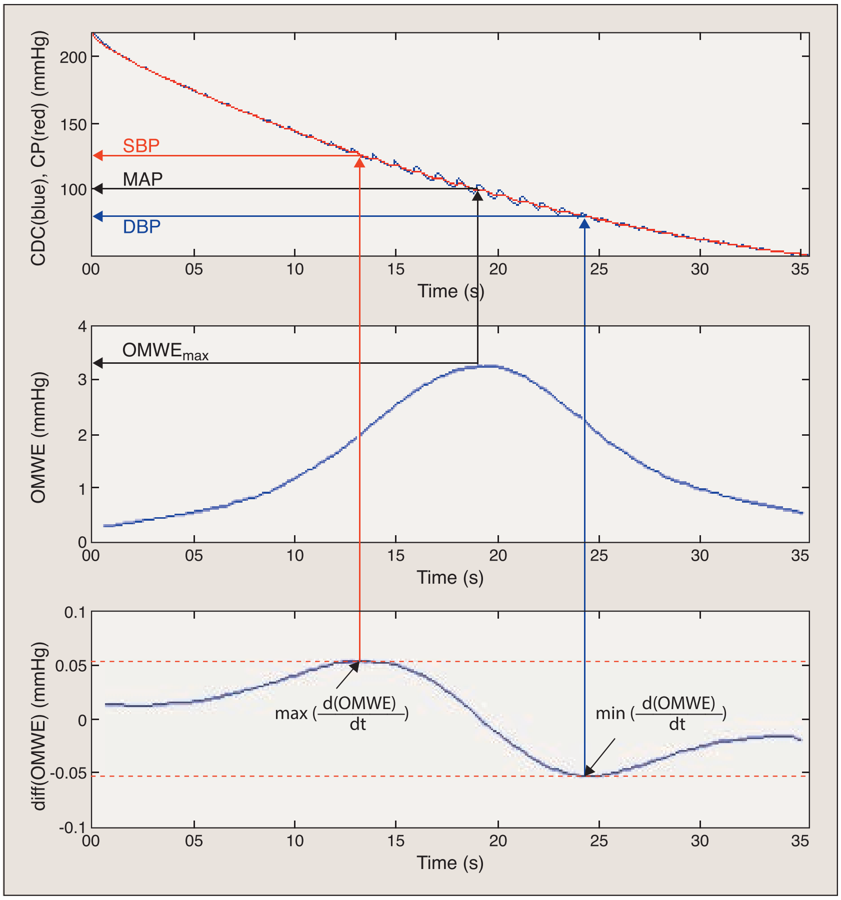

Fig. 6. Procedure of the maximum/minimum slope algorithm (MMSA). Cuff deflation curve (up-blue) is shown as a sample BP recording. Cuff pressure (up-red) is extracted using the detrending method. OMWE (middle). CP at which the smoothed OMWE attains maximum is determined as MAP. Cuff pressure at which the amplitude of the first derivative of the OMWE becomes maximum is determined as SBP. Cuff pressure at which the amplitude of the first derivative of the OMWE is minimum is determined as DBP.

Experimental Results

To conduct the experiments and validate the results, three different datasets are employed and BP is estimated by MAA and MMSA algorithms. DTA was applied to the results and untrusted recordings were detected and removed as outliers. Mean absolute error (MAE) and standard deviation of errors (STDE) from the references were estimated and compared with corresponding results before removing the outliers from datasets. Results are shown in Tables 1 to 3. Moreover, one subject with an outlier is selected randomly and analyzed to observe similar results over a single subject.

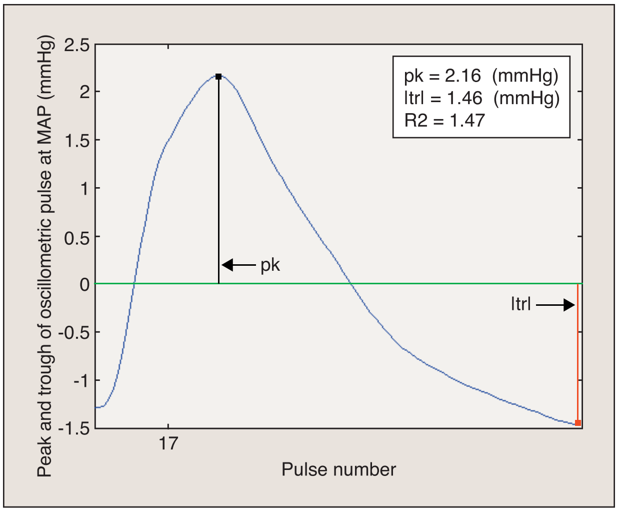

Fig. 7. Oscillometric pulse at MAP ($PULSE_{MAP}$) for one sample recording which is the 17th pulse of the OMW. Peak (pk) and trough (|tr|) amplitudes are determined to calculate amplitude ratio (R2).

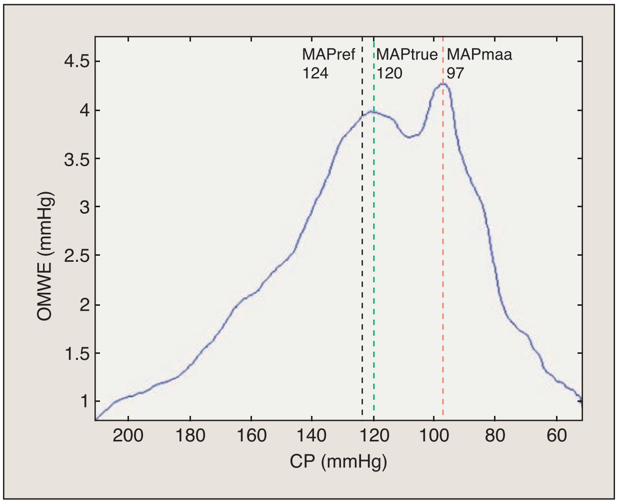

Fig. 8. Smoothed OMWE of a sample recording with false maximum estimated by MAA at CP=97 mmHg. Reference MAP is at CP=124 mmHg, so the true maximum should be at CP=120 mmHg which is much closer to reference MAP (MAP_{ref}).

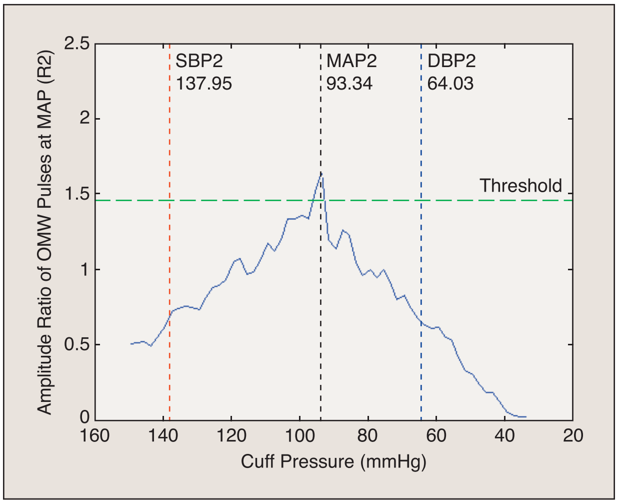

Fig. 9. Amplitude ratio of oscillometric pulses at MAP for a sample recording,

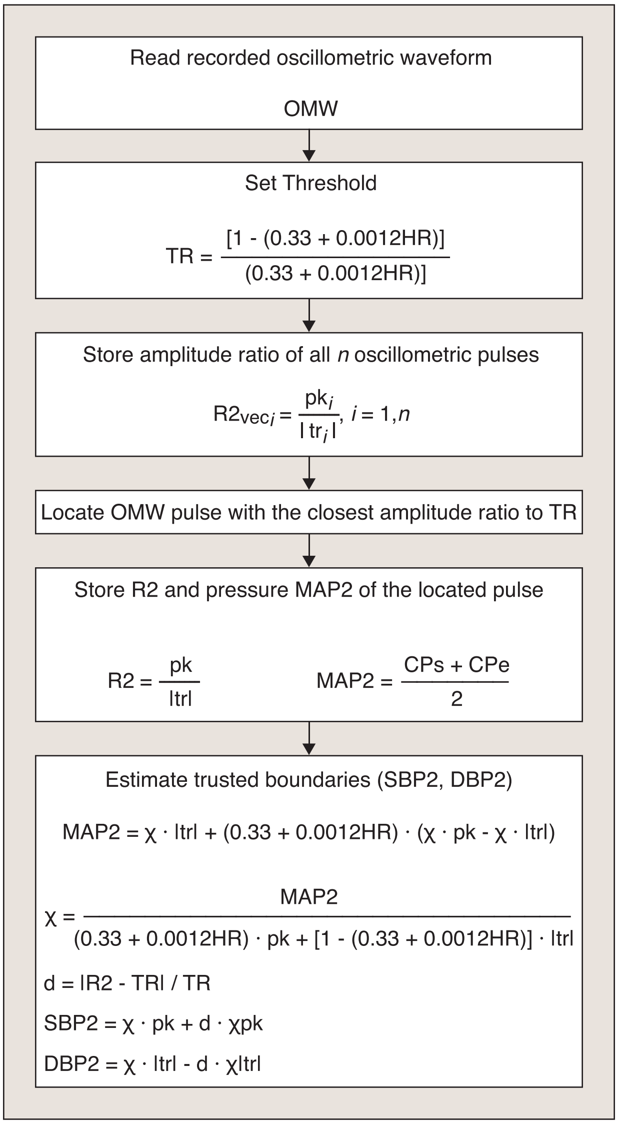

Fig. 10. Dynamic Threshold Algorithm (DTA). OMW is extracted from CDC by detrending method.

Dataset 1 (DS1)

DS1 is the first oscillometric waveform dataset acquired using an automated wrist BP monitor (UFIT TEN-10 by Biosign Technologies Inc.) in accord with the recommendations of the ANSI/AMMI/ISO standard [20]. The dataset includes 85 healthy subjects, 48 males and 37 females, aged from 12 to 80. Five sets of oscillometric wrist BP measurements were obtained from each subject, resulting in a total of 425 measurements. A double stethoscope system was used to collect reference values by two trained observers. The average value of these two measurements was used as the reference pressure of each subject for the corresponding trial.

Dataset 2 (DS2)

DS2 is composed of 150 simultaneous oscillometric BP and ECG that were acquired using the prototype designed in our research laboratory [21] and a Food and Drug Administration (FDA) - approved Omron monitor (HEM-790IT) for reference

Table 1 – Validated results and improvements for DS1 before and after removing the outliers over 1 and 85 healthy subjects												
DS1	Results from MAA						Results from MMSA					
	Before (mmHg)		After (mmHg)		Improvements %		Before (mmHg)		After (mmHg)		Improvements %	
	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP
One Subject												
MAE	9.32	2.61	7.84	2.52	15.93	3.54	19.43	7.79	12.63	3.96	35.01	49.09
STDE	3.11	1.33	2.49	0.20	20.02	84.67	9.23	11.53	0.49	4.47	94.65	61.22
425 Recordings												
MAE	7.50	5.59	7.30	5.03	2.65	10.06	13.72	6.98	11.56	5.66	15.79	18.81
STDE	6.80	4.84	5.39	4.62	20.76	4.49	10.22	6.32	7.18	4.87	29.74	22.94

Table 2 – Validated results and improvements for DS2 before and after removing the outliers over 1 and 10 healthy subjects												
DS2	Results from MAA						Results from MMSA					
	Before (mmHg)		After (mmHg)		Improvements %		Before (mmHg)		After (mmHg)		Improvements %	
	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP
One Subject												
MAE	9.51	1.83	9.33	1.81	1.88	1.02	5.97	1.80	5.88	1.73	1.57	3.94
STDE	2.25	0.93	2.07	0.77	7.90	17.25	2.75	0.86	2.32	0.78	15.60	9.35
150 Recordings												
MAE	5.66	3.35	5.45	3.31	3.76	1.16	6.17	4.59	6.11	3.67	0.93	20.14
STDE	4.59	2.75	4.25	2.71	7.36	1.53	5.14	4.76	5.03	2.97	2.11	37.54

Table 3–Validated results and improvements for DS3 before and after removing the outliers over 1 and 13 sick subjects												
DS3	Results from MAA						Results from MMSA					
	Before (mmHg)		After (mmHg)		Improvements %		Before (mmHg)		After (mmHg)		Improvements %	
	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP	SBP	DBP
One Subject												
MAE	10.78	14.11	9.17	13.43	14.91	4.85	8.23	5.31	6.31	3.32	23.30	37.50
STDE	6.55	5.18	2.44	4.15	62.79	19.85	5.66	4.16	4.91	1.42	13.26	65.73
78 Recordings												
MAE	12.20	8.40	11.64	6.61	4.62	21.28	8.98	7.88	7.23	5.88	19.52	25.40
STDE	8.36	5.22	7.54	4.22	9.84	19.08	8.92	5.26	6.27	4.87	29.70	7.47

measurements. This study was approved by the University of Ottawa Research Ethics Board, and written informed consent was obtained from all subjects. The dataset includes 10 healthy subjects, 6 males and 4 females, aged from 24 to 63. Five sets of oscillometric arm BP measurements were obtained in three days from each subject, resulting in a total of 150 measurements. The subjects also wore a wristband on the right wrist for simultaneous ECG recording.

Dataset 3 (DS3)

DS3 is composed of 78 simultaneous oscillometric BP and ECG recordings from sick patients with various chronic conditions including atrial fibrillation, hypertension, and obesity. The dataset was acquired using Health Parametrics Inc. (HPI) prototype (EABPM-01) using an arm cuff and a clinically standard arm BpTru monitor (BPM-100) for reference measurements. The dataset includes 13 sick subjects, 5 males and 8 females, aged from 46 to 85. Two dry flexible electrodes made of conductive fabric inside the cuff along with a handle attached to the device were used for simultaneous ECG recording.

Trustworthiness Evaluation of Estimated BP

Accuracy of the BP estimators is not the focus of this research, as we are not proposing any BP estimation algorithm but rather the DTA that determines the trustworthiness of the measured BP in oscillometric monitors. Improper measuring conditions and inaccurate BP estimation algorithms affect the trustworthiness of the BP readings. The objective of the experiments is to validate the estimated BP against corresponding references before and after removing the outliers from the datasets and to compare the results to observe improvements in accuracy of the results. To this end, DTA was applied to the estimated BP, outliers were detected and removed from the datasets, and results were validated against references for each dataset, and compared with validated results before removing the outliers.

The DS1 oscillometric recording device returns two waveforms: the deflating cuff pressure (CP) and the discrete derivative of the CDC which we used to extract the OMW. CDC was retrieved by integrating the derivative of the input recorded CDC, and a detrending method was employed to extract OMW by subtracting recorded CP samples from corresponding CDC samples. OMWE was formed by subtracting the peak of each oscillometric pulse from the corresponding trough sample.

$$OMW = CDC - CP \tag{11}$$

$$OMWE = pk - tr \tag{12}$$

Two MAA and MMSA estimation algorithms were employed to estimate BP from OMWE. BP was estimated in terms of the SBP and DBP for each estimation algorithm over 425 recordings. Results were validated against nurse references, and absolute differences from references (MAE) were estimated along with the standard deviation of the differences (STDE) for all subjects. Next, DTA was applied, upper and lower limits (SBP2, DBP2) of trusted boundaries were determined for each recording, and the results were compared with the pressures SBP and DBP estimated by the two MAA and MMSA algorithms. Estimated pressures were considered trusted if inside the trusted boundaries. Otherwise, they were considered as outliers and were removed from the dataset. For MAA, 129 and 49 outliers were found in terms of SBP and DBP, respectively, while it was 213 and 75 for the MMSA algorithm. The remaining dataset was validated against nurse references, and MAE and STDE were estimated again and compared with the corresponding values before removing the outliers. Validated results and improvements for DS1 are shown in Table 1.

For more confidence in the results and level of improvements, DTA was tested on another healthy dataset (DS2). The whole procedure was the same as for DS1, except OMW was obtained from the recorded CDC using a 2nd order band-pass digital Butterworth filter with the lower cutoff frequency of 0.5 Hz and upper cutoff frequency of 20 Hz. For MAA, 6 and 0 outliers were found in terms of SBP and DBP, respectively, while it was 4 and 9 for MMSA algorithm. Validated results and improvements for DS2 are shown in Table 2.

To investigate the performance of the DTA on sick subjects, DS3 was acquired from 78 patients with chronic conditions such as hypertension, obesity, and atrial fibrillation. The whole procedure was the same as DS2 with the same filtering approach to obtain OMW from the CDC. For MAA, 38 and 0 outliers were found in terms of SBP and DBP, respectively, while it was 27 and 0 for MMSA algorithm. Validated results and improvements for DS3 are shown in Table 3.

Uncertainty Analysis of DTA

Uncertainty can be evaluated statistically to provide a confidence interval (CI). Confidence interval is defined as a "margin within which the 'true value' being measured can be said to lie, with a given level of confidence" [22]. Level of confidence expresses the degree of confidence in the result. Standard uncertainty u(x) is obtained from square root of variance of the measurements for measurand 'x'. To find the CI, a coverage factor (K) is required to be multiplied by u(x) and provide expanded uncertainty U. The coverage factor depends on the probability density function of the measurand. For example, let the measurand distribute according to a normal distribution about mean value $\bar{x}$ over n samples. The standard uncertainty $u(x)$ is given by standard deviation σ of this distribution. If K=1, then $CI = \bar{x} \pm \sigma$ at a level of confidence of 68.3%. If K=2, then $CI = \bar{x} \pm 2\sigma$ at a level of confidence of 95%. Similarly, if K=3, then $CI = \bar{x} \pm 3\sigma$ at a level of confidence of 99.7% [23].

$$u(x) = \sqrt{\frac{\sigma_x^2}{n}} \tag{13}$$

$$U = Ku(x) \tag{14}$$

$$CI = \bar{x} \pm U \tag{15}$$

To show how DTA improves uncertainty of the measurements, we estimated uncertainty of the measurements before and after applying the DTA and compared them to estimate the level of the improvements in uncertainty. Improvements are shown in Table 4.

Conclusion

Non-invasive blood pressure oscillometric monitors are a popular alternative for the auscultatory method which is still considered as the golden standard and widely used in HBMS. Although current oscillometric monitors have successfully fulfilled the validation protocols developed by the International Organization for Standardization, the American Association

Table 4 – Improvements of uncertainty caused by DTA for both estimation algorithms

All Subjects	MAA		MMSA	
	Improvements %		Improvements %	
	SBP	DBP	SBP	DBP
Uncertainty (U)				
DS1 (425)	5.05	1.06	0.52	15.09
DS2 (150)	5.45	1.53	0.77	35.58
DS3 (78)	4.82	19.08	13.06	7.47

for the Advancement of Medical Instrumentation [24], or the British Hypertension Society [25], they fail to provide trustable BP measurements in some cases [26]. Even with the most accurate oscillometric monitors one can get different BP readings if BP is measured repeatedly. The most frequent reasons are the measuring conditions of the patients, nonlinear properties of the cardiovascular system such as vessel compliance, nonlinear behavior of the cuff system especially the cuff itself, motion artifacts, and environmental noise. As a result, patients do not know how to trust different BP readings. To this end, DTA is proposed to provide information about trustworthiness of the measured BP, so patients have the option whether to repeat the measurement or not. DTA estimates upper and lower limits for estimated SBP and DBP, respectively as trusted boundaries and compares the estimated BP with determined boundaries. Measured BP is trustable if both SBP and DBP are inside the trusted boundaries. Otherwise, the measurement is untrusted and patient should ignore the measurement. In this research, a new algorithm (DTA) was applied on three different datasets composed of healthy and sick subjects with cardiovascular conditions, and untrusted recordings called outliers were detected and removed from the datasets. Results were validated against references before and after removing the outliers and compared to determine the level of improvements attained by DTA.

According to the results listed in Tables 1–3, we observed up to 15.93%, 3.54% improvements in MAE with 20.02%, 84.67% improvements in STDE for SBP and DBP estimated by MAA, respectively, for healthy subjects. Similarly, improvements were up to 35.01%, 49.09% in MAE with 94.65%, 61.22% in STDE for SBP and DBP estimated by MMSA, respectively, for the healthy subjects.

Also, we observed up to 14.91%, 4.85% improvements in MAE with 62.79%, 19.85% improvements in STDE for SBP and DBP estimated by MAA, respectively, for the sick subjects. Similarly, improvements were up to 23.30%, 37.50% in MAE with 13.26%, 65.73% in STDE for SBP and DBP estimated by MMSA, respectively, for the sick subjects. Moreover, DTA could reduce uncertainty of the measurements up to 13.06%, 35.58% for SBP and DBP, respectively.

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