# Electrocardiogram-Assisted Blood Pressure Estimation

Saif Ahmad*, Silu Chen, Karen Soueidan, *Member, IEEE*, Izmail Batkin, Miodrag Bolic, *Senior Member, IEEE*, Hilmi Dajani, *Senior Member, IEEE*, and Voicu Groza, *Senior Member, IEEE*

***Abstract*—Accurate automatic noninvasive assessment of blood pressure (BP) presents a challenge due to conditions like arrhythmias, obesity, and postural changes that tend to obfuscate arterial amplitude pulsations sensed by the cuff. Researchers tried to overcome this challenge by analyzing oscillometric pulses with the aid of a higher fidelity signal—the electrocardiogram (ECG). Moreover, pulse transit time (PTT) was employed to provide an additional method for BP estimation. However, these methods were not fully developed, suitably integrated, or tested. To address these issues, we present a novel method whereby ECG-assisted oscillometric and PTT (measured between ECG *R*-peaks and maximum slope of arterial pulse peaks) analyses are seamlessly integrated into the oscillometric BP measurement paradigm. The method bolsters oscillometric analysis (amplitude modulation) with more reliable ECG *R*-peaks provides a complementary measure with PTT analysis (temporal modulation) and fuses this information for robust BP estimation. We have integrated this technology into a prototype that comprises a BP cuff with an embedded conductive fabric ECG electrode, associated hardware, and algorithms. A pilot study has been undertaken on ten healthy subjects (150 recordings) to validate the performance of our prototype against United States Food and Drug Administration approved Omron oscillometric monitor (HEM-790IT). Our prototype achieves mean absolute difference of less than 5 mmHg and grade A as per the British Hypertension Society protocol for estimating BP, with the reference Omron monitor.**

***Index Terms*—Blood pressure estimation, cuff pressure (CP), electrocardiogram (ECG), oscillometric analysis, pulse transit time (PTT).**

## I. Introduction

BLOOD pressure (BP), defined as the pressure exerted by circulating blood upon the walls of blood vessels, is an important biomarker of cardiovascular health [1]. Accurate measurement of BP employing noninvasive methods such as Korotkoff sounds [2] and oscillometry [3] is a challenge. Factors like arrhythmias, obesity, and postural changes tend to obscure arterial amplitude pulsations that are sensed by a cuff (or by a stethoscope), thus introducing errors in these measurements [4]–[9]. Therefore, robust and reliable noninvasive estimation of BP remains a topic of active research and inquiry.

With advances in computing power and digital signal processing, computer-based (automatic) assessment of BP has received much attention. Scientists have explored newer methods that not only bolster the popular oscillometric technique but also go beyond it for estimating BP. The analysis of an oscillometric signal along with a simultaneously acquired electrocardiogram (ECG) signal promises to increase the robustness of oscillometric BP estimation. This is because the higher fidelity and more consistent ECG signal assists in the identification of true cardiac pulses in an oscillometric signal that may be contaminated with noise and artifacts—thus lending greater trustworthiness to the oscillometric BP estimation. For example, the use of an ECG signal was proposed for reconstructing an oscillometric signal contaminated with artifacts to provide accurate assessment of BP [10]. Similarly, synchronized ECG signals were employed for removing motion artifacts from oscillometric signals to increase the accuracy of BP measurements [11].

A widely researched method that goes beyond oscillometry comprises the estimation of BP from pulse transit time (PTT)—the time taken by a cardiac pulse to travel between the heart and a peripheral arterial site or between two peripheral arterial sites [12]–[14]. A review of relevant literature suggests that assessment of BP from PTT can be broadly classified into two categories, namely, PTT-BP correlation analysis and PTT-cuff pressure (CP) analysis. Briefly, PTT $\tau$ can be considered to be composed of two additive components, $\tau_0$ and $\tau_c$:

$$\tau = \tau_0 + \tau_c. \tag{1}$$

In (1), $\tau_0$ is the baseline PTT related to the pressure the blood exerts on the arteries, whereas $\tau_c$ is the change in PTT observed as a response to the applied CP.

The PTT-BP correlation analysis method assesses BP by utilizing the inverse correlation between PTT and BP whereby a rise in BP causes the PTT to decrease and vice versa. Here, no CP is applied while measuring PTT and hence $\tau_c = 0$, which implies $\tau = \tau_0$ [from (1)]. The PTT is measured based on an ECG signal and an arterial pulse wave signal recorded from a convenient site or based on two arterial pulse wave signals recorded from two different sites. An additional automatic or

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*S. Ahmad is with the School of Electrical Engineering and Computer Science, University of Ottawa, 800 King Edward Avenue, Ottawa, ON K1N 6N5, Canada (e-mail: sahmad@site.uottawa.ca).

S. Chen was with the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON K1N 6N5, Canada. He is now with Research In Motion, Waterloo, ON N2L 3L3, Canada (e-mail: sc85.23@gmail.com).

K. Soueidan is with the University of Ottawa Heart Institute, Ottawa, ON K1Y 4W7, Canada (e-mail: karen.soueidan@gmail.com).

I. Batkin is with the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON K1N 6N5, Canada and with Ottawa General Hospital, Ottawa, ON K1H 8LC, Canada (e-mail: vbatkin@rogers.com).

M. Bolic, H. Dajani, and V. Groza are with the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON K1N 6N5, Canada (e-mail: mbolic@site.uottawa.ca; hdajani@site.uottawa.ca; groza@site.uottawa.ca).

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manual sphygmomanometer is employed for measuring BP independently. A linear regression model is built between PTT and independently measured BP values. Once sufficient data have been collected, the linear regression model is used to predict future BP values based on new PTT values. A number of studies explored the PTT-BP correlation analysis method with varied success rates [15]–[21]. However, this method suffers from two major limitations. First, it requires frequent calibration using a reference sphygmomanometer, thus making the procedure complicated and cumbersome. Second, PTT-BP correlations are generally weak and inconsistent [22]–[24]. Therefore, the PTT-BP correlation analysis method cannot be reliably used for accurate measurement of BP.

The PTT-CP analysis method studies the response of PTT to changing CP for assessing BP. It has been observed that the magnitude of PTT changes in response to applied CP when PTT is measured from an arterial pulse wave signal recorded near the cuff [see (1)]. The relationship between the CP-dependent component of PTT $\tau_c$, arterial diameter $d$, applied CP $P_{\mathrm{CP}}$, internal $P_0$, and elastic modulus of artery under equilibrium $\lambda_0$ is as follows [14]:

$$\tau_c \, \alpha \sqrt{\frac{d}{|P_{\mathrm{CP}} - P_0| + \lambda_0}}. \tag{2}$$

As a result, PTT changes in response to the changing CP [see (1) and (2)] and the shape of the PTT-CP plot is utilized for estimating BP. Since this is a direct method of estimating BP from PTT, it shows more promise.

The first study that employed the PTT-CP analysis method was performed on dogs by Geddes *et al*. [25]. ECG data were recorded employing a lead II configuration, and arterial pulses were recorded invasively near an infant brachial cuff that was wrapped around the forelimb of the dog. The cuff was inflated to a pressure above the expected systolic pressure (SP) and then deflated at a constant rate of 1 mmHg/s. PTT was measured between ECG *R*-peaks and arterial pulses during cuff deflation. No pulse and, hence, no PTT were detectable when the CP was above SP. From SP onwards, when pulses started to appear, PTT decreased linearly with decreasing CP but only up to a certain point—the diastolic pressure (DP). From DP onwards, PTT remained constant with decreasing CP, i.e., the PTT attained saturation. The CP at which a pulse first appeared and PTT was measurable was defined as SP, while the CP at which PTT attained saturation was defined as DP.

Sharir *et al*. [26] estimated DP and SP noninvasively in humans employing a method similar to Geddes *et al*. [25]. PTT was measured between an ECG signal and an arterial pulse wave signal that was recorded using a Doppler probe near the brachial cuff. Results were validated using invasive BP estimation. Sorvoja *et al*. [27] also employed a similar method for estimating DP and SP in humans. They measured PTT between two arterial pulse wave signals that were recorded at the left and right wrists. Results were validated using an oscillometric as well as an invasive BP estimation method. The PTT-CP dependence observed by Sharir *et al*. [26] and Sorvoja *et al*. [27] was in conformity with the one described by Geddes *et al*. [25]. On the other hand, Kerola *et al*. [28] employed two piezoelectric pulse sensors separated by some distance under a brachial cuff to study the PTT-CP dependence for estimating BP in humans. They observed that for decreasing CP, PTT first increased and then decreased. The CP at which PTT attained its maximum value was defined as SP, while the CP at which it attained a slope close to zero was defined as DP.

Previous work indicated that an ECG signal could be used for increasing the accuracy of oscillometric BP estimation [10], [11]. However, the simultaneously acquired ECG and oscillometric signals were not utilized for studying the PTT-CP dependence to provide additional assessment of BP. Conversely, the studies that employed the PTT-CP analysis for estimating BP [25]–[28] failed to integrate the oscillometric BP estimation technique with this method. In these studies, the brachial cuff was used only for occluding the arteries while additional sensors were employed for sensing arterial pulses. In fact, all of the aforementioned protocols [10], [11], [25]–[28] require a number of auxiliary pressure and/or ECG sensors to be attached to the subject in addition to the brachial BP cuff, thus making them obtrusive and inconvenient. Finally, most of the aforementioned protocols were not adequately validated.

To address the aforementioned problems, we propose a novel method whereby an ECG-assisted oscillometric analysis and a PTT-CP analysis are seamlessly integrated into the oscillometric BP monitoring paradigm. This method reinforces oscillometric analysis, which is an amplitude modulation technique, by providing ECG *R*-peaks for better oscillometric pulse peak detection and BP estimation. It provides a complementary measure of BP with PTT-CP analysis, which is a temporal modulation technique. Finally, it fuses information from these diverse techniques for robust BP estimation. To accomplish this, we have developed a prototype of an integrated blood pressure and electrocardiogram monitor (InBeam). The design of the InBeam prototype is based on a simple modification of the conventional oscillometric BP monitor. It employs a dry and flexible ECG electrode incorporated inside a brachial BP cuff, which coupled with appropriate hardware and software enables the cuff to simultaneously harvest ECG and CP signals during a relatively unobtrusive BP measurement. The ECG *R*-peaks are used to detrend the CP signal for obtaining an oscillometric signal. In addition, the ECG *R*-peaks are used for finding oscillometric pulse peaks and troughs, following which BP is estimated utilizing the maximum amplitude method [3]. PTT is measured between the ECG *R*-peaks and the maximum slope of the oscillometric pulses. A PTT-CP analysis akin to the maximum amplitude method is employed to obtain an auxiliary estimation of BP. Finally, results from the oscillometric and PTT-CP analysis methods are fused to provide a robust and reliable assessment of BP.

An earlier version of the InBeam prototype was presented in [29]. We showed that it is possible to acquire ECG and arterial pulse wave signals simultaneously by embedding an ECG electrode inside a brachial BP cuff and coupling it with appropriate hardware/software. Here, we extend that work by 1) developing new algorithms for ECG-assisted BP measurement, 2) validating the prototype and algorithms with a larger number

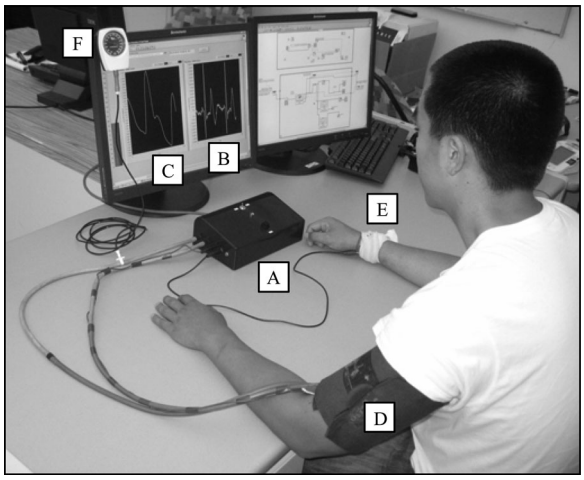


Fig. 1. InBeam prototype (A) harvesting ECG (B) and CP (C) signals from a male subject during cuff deflation. A brachial cuff with an embedded flexible ECG electrode (D) is wrapped around the subject's left arm. A wristband with the second embedded flexible ECG electrode (E) is wrapped around the subject's right wrist. Air hoses and electrical leads connect the cuff and the wristband to the prototype. A mechanical pressure gauge (F) is connected to one of the hoses using a T-connector for periodically validating the calibration of the InBeam prototype.

of subjects and measurements, 3) designing and fabricating our own ECG circuitry, 4) providing motorized cuff inflation and manual cuff deflation to enable oscillometric measurement, and 5) rendering the prototype more compact by incorporating all components inside a single device box.

In this paper, we present a description of the InBeam prototype and related algorithms. We undertake a pilot study to validate the performance of the InBeam prototype vis-à-vis the United States Food and Drug Administration (FDA)-approved Omron oscillometric BP monitor (HEM-790IT) [30]–[32]. We analyze 150 recordings obtained from ten healthy subjects using the InBeam prototype and the Omron BP monitor. The InBeam prototype achieves a mean absolute difference (MAD) of $3.31 \pm 2.16$ mmHg for DP, $2.36 \pm 1.90$ mmHg for mean arterial pressure (MAP), and $4.06 \pm 3.25$ mmHg for SP with corresponding estimates made by the Omron device. Moreover, it achieves a grade A for DP, MAP, and SP estimation according to the British Hypertension Society (BHS) protocol [33] as per the reference Omron monitor.

## II. Methods

### A. InBeam Prototype

Fig. 1 shows a picture of the InBeam prototype harvesting simultaneous ECG and CP signals from the left arm and right wrist of a male subject. The prototype acquires these signals during cuff deflation, similar to a conventional oscillometric BP monitor. A strip of thin and flexible conductive fabric is incorporated on the inner side of an adult brachial cuff, which is wrapped around the subject's arm (left arm in this case). This renders the brachial cuff as the first ECG electrode as well as a sensor for arterial pulses. Another small strip of conductive fabric is incorporated on the inner side of an ordinary wristband, which is wrapped around the wrist of the subject's other hand (right wrist in this case). This wristband acts as the second ECG electrode. More details about the design of the cuff and the wristband can be found in [29]. The cuff and wristband are connected to the prototype through two air hoses and two electrical leads.

A cable connects the prototype via National Instruments (Austin, TX) data acquisition hardware to a personal computer (PC) where the acquired ECG and oscillometric signals are stored and analyzed. The picture in Fig. 1 also shows a medical grade mechanical pressure gauge (Tycos Aneroid Sphygmomanometer, Mexico) connected to one of the hoses of the InBeam prototype using a T-connector. This mechanical pressure gauge is used for periodically validating the calibration of the prototype.

The InBeam prototype unit contains four main components, namely, an analog ECG amplifier, an analog pressure transducer, a mini dc air pump, and a screw-controlled manual pressure release valve. The ECG amplifier, which we have designed and fabricated, is used for acquiring analog ECG data. The two ECG leads—one from the brachial cuff and one from the wristband—form the input to the ECG amplifier. This is equivalent to a lead 1 configuration. The ECG amplifier has an input impedance of 20 M$\Omega$ and a voltage gain of one. The core of the ECG amplifier consists of an instrumentation amplifier (INA-129, Texas Instruments, Dallas, TX) supported by circuitry for stabilizing the supply voltage and for signal conditioning. The ECG amplifier operates on a dc supply voltage of $\pm 5$ V and outputs an analog ECG signal in the range of 20–2000 $\mu$V.

We use a Vernier pressure transducer (BPS-BTA, Beaverton, OR) for converting arterial pulse wave data into an analog voltage signal. The first hose from the brachial cuff forms the input to the pressure transducer. The Vernier pressure transducer operates on a dc supply voltage of 5 V and converts mechanical vibrations in the cuff (produced due to arterial BP) to an analog output voltage signal in the range of 0–5 V, which corresponds to an input pressure range of 0–250 mmHg.

A 6-V dc mini air pump is used for inflating the brachial cuff. The second hose from the brachial cuff is connected to the mini air pump. Keeping a normally open pushbutton depressed on the InBeam prototype unit operates the mini air pump which, in turn, inflates the brachial cuff.

The screw-controlled manual pressure release valve is connected in-line with the brachial cuff, the analog pressure transducer, and the mini dc air pump. The screw on the valve can be rotated clockwise and anticlockwise for controlling the deflation rate of the cuff.

The analog voltage outputs from the ECG amplifier and the Vernier pressure transducer are fed to two of the four simultaneously sampled analog input channels of a National Instruments C Series 9239 analog input module (NI-9239) mounted on a CompactDAQ data acquisition board. Passing through the NI-9239 module, these analog signals are conditioned, buffered, and then sampled by a 24-bit delta-sigma analog-to-digital converter. The quantized signals are transmitted to a PC via a USB cable.

The voltage to the Vernier pressure transducer is supplied by a National Instruments C Series 9263 4-Channel, 16-bit, $\pm$10-V

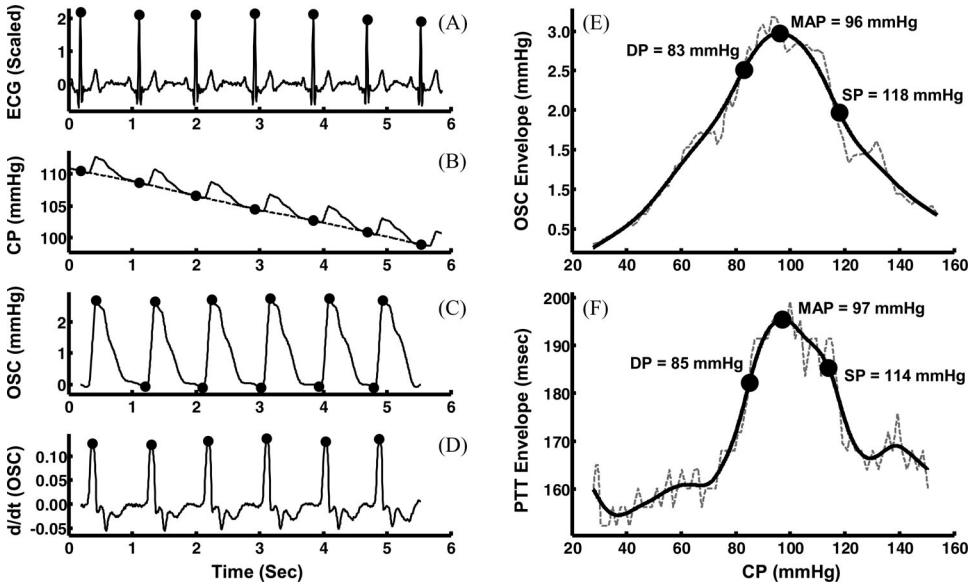


Fig. 2. Graphical description of the ECG-assisted oscillometric analysis algorithm and the PTT-CP analysis algorithm. For clarity of display, plots on the left show a 6-s section of the (Plot A) ECG and (Plot B) CP signals acquired by the (Plots C and D) InBeam prototype and their analysis. Plots on the right show the (Plot E) complete oscillometric and (Plot F) PTT envelopes derived from these signals and the estimation of BP from them. See algorithms in Figs. 3 and 4 for more details.

analog output module (NI-9263) mounted on the CompactDAQ data acquisition board. On the other hand, the voltages to the ECG amplifier and the mini air pump are supplied by two separate external battery packs. To ensure a constant and accurate voltage supply over time to the pressure transducer and hence a dependable calibration, it is powered by the NI-9263 module. The ECG amplifier is powered by a battery pack to minimize the effects of 60-Hz power line frequency interference in the ECG signal. The choice of powering the air pump by yet another battery pack is for convenience and simplicity of procedure.

We use the National Instruments LabVIEW development environment for acquiring and controlling the acquisition of ECG and CP signals using a PC. Both signals are acquired simultaneously at a sampling rate of 1000 Hz.

We have written software in MATLAB (The MathWorks Inc., Natick, MA) for reading, processing, and analyzing the acquired ECG and CP signals.

### *B. ECG-Assisted Oscillometric Analysis Algorithm*

A graphical description of the ECG-assisted oscillometric algorithm and the PTT-CP analysis algorithm is presented in Fig. 2. Plots on the left show a 6-s section of the ECG and CP signals acquired by the InBeam prototype during cuff deflation and their analysis (Plots A–D). Plots on the right show the entire oscillometric and PTT envelopes derived from these signals and the estimation of BP from them (Plots D–F).

The first step of the ECG-assisted oscillometric analysis algorithm involves identification of ECG *R*-peaks (dots, Plot A, Fig. 2). We identify ECG *R*-peaks using the MIT/PhysioNET MATLAB QRS onset detector software [34], [35]. This is followed by superimposing temporal locations of ECG *R*-peaks on the CP signal (dots, Plot B, Fig. 2). A CP trend line is obtained (dotted line, Plot B, Fig. 2) using ECG *R*-peak information and is used to detrend the CP signal to obtain an oscillometric signal (solid line, Plot C, Fig. 2). The ECG *R*-peak information is also used for finding peaks in the oscillometric signal (upper dots, Plot C, Fig. 2)—the maximum amplitude of the oscillometric signal between every two consecutive ECG *R*-peaks is determined. The oscillometric pulse peak information is used for finding troughs in the oscillometric signal (lower dots, Plot C, Fig. 2)—the minimum amplitude of the oscillometric signal between every two consecutive oscillometric pulse peaks is determined. Amplitudes of the oscillometric pulse troughs are subtracted from amplitudes of the oscillometric pulse peaks and corresponding CPs are determined to obtain the oscillometric envelope (dotted line, Plot E, Fig. 2).

The oscillometric envelope is interpolated and then smoothed using a cubic smoothing spline function (solid line, Plot E, Fig. 2). This is followed by estimating MAP, DP, and SP employing the maximum amplitude method [3]. The DP and SP estimation coefficients that we use are 0.84 and 0.66, respectively. Both these coefficients were determined empirically. Once DP and SP have been estimated using the maximum amplitude method, we also compute a formula-based MAP [36], i.e., $\text{MAP} = \text{DP} + 1/3 \times (\text{SP} - \text{DP})$. We compute the formula-based MAP for the InBeam device to allow for an equivalent comparison with the Omron MAP value which we also calculate using the same formula (since the Omron monitor only outputs DP and SP values). For details, see Fig. 3 showing the ECG-assisted oscillometric algorithm.

### *C. PTT-CP Analysis Algorithm*

The PTT-CP analysis algorithm follows from the ECG-assisted oscillometric algorithm. First, the derivative (solid line, Plot D, Fig. 2) of the oscillometric signal (solid line, Plot C, Fig. 2) is obtained. Then, ECG *R*-peak information (dots, Plots

1. Detect ECG R-peaks (dots, Plot A).
2. Find points (ordinates) on the CP signal corresponding to the temporal positions (abscissas) of ECG R-peaks (dots, Plot B).
3. Linearly interpolate the points on the CP signal that correspond to the ECG R-peaks (dots, Plot B) with temporal positions (abscissas) of the ECG signal to obtain a trend line for the CP signal (dotted line, Plot B).
4. Subtract the ordinates of the CP trend line (dotted line, Plot B) from the ordinates of CP signal (solid line, Plot B) for matching abscissas to obtain an oscillometric signal (solid line, Plot C).
5. Find peaks in the oscillometric signal: find the maxima of the oscillometric signal ordinates (upper dots, Plot C) that lie between every two consecutive ECG R-peak abscissas (dots, Plot A) and determine their corresponding abscissas.
6. Find troughs in the oscillometric signal: find the minima of the oscillometric signal ordinates (lower dots, Plot C) that lie between every two consecutive oscillometric peak abscissas (upper dots, Plot C) and determine their corresponding abscissas.
7. Subtract the oscillometric signal trough ordinates (lower dots, Plot C) from the oscillometric signal peak ordinates (upper dots, Plots C) to obtain ordinates of the oscillometric envelope. Find the CP trend line ordinates (dotted line, Plot B) that correspond to the oscillometric peak abscissas (upper dots, Plot C) to obtain abscissas of the oscillometric envelope (dotted grey lines, Plot E).
8. Linearly interpolate the oscillometric envelope with an abscissa (CP) sampling rate of 0.01 mmHg.
9. Smooth the oscillometric envelope using a cubic smoothing spline function (solid black line, Plot E).
10. Find the maximum value of the ordinates of the smoothed oscillometric envelope and read off the corresponding abscissa to determine MAP (middle dot, Plot E).
11. Find an ordinate on the oscillometric envelope (for abscissas less than the MAP abscissa) that is 84 % of the MAP ordinate. Read off the corresponding abscissa of this ordinate to determine DP.
12. Find an ordinate on the oscillometric envelope (for abscissas greater than the MAP abscissa) that is 66 % of the MAP ordinate. Read off the corresponding abscissa of this ordinate to determine SP.
13. Estimate formula-based mean arterial pressure, $MAP = DP + 1/3 \times (SP - DP)$.

Fig. 3. ECG-assisted oscillometric analysis algorithm.

A, Fig. 2) is used to find peaks in the derivative of the oscillometric signal (upper dots, Plot D, Fig. 2)—the maximum amplitude of the derivative of the oscillometric signal between every two consecutive ECG *R*-peaks is determined. This is followed by measuring PTT in milliseconds between ECG *R*-peaks and peaks of the derivative of the oscillometric signal and determining the corresponding CP to obtain the PTT envelope (dotted line, Plot F, Fig. 2).

The PTT envelope is interpolated, after which a cubic smoothing spline function is used to smooth it (solid line, Plot F, Fig. 2). Since the shape of the PTT envelope is similar to that of the oscillometric envelope (Plots E and F, Fig. 2), a technique analogous to the maximum amplitude method [3] is employed for estimating MAP, DP, and SP. In this case, we use DP and SP estimation coefficients of 0.93 and 0.95, respectively. Again, both these coefficients were determined empirically. Finally, MAP is computed using the formula $\mathrm{MAP} = \mathrm{DP} + 1/3 \times (\mathrm{SP} - \mathrm{DP})$. For details, see the PTT-CP analysis algorithm presented in Fig. 4.

### D. Fusion Algorithm

To obtain a stable and robust estimation of BP, we fuse the information obtained from the ECG-assisted oscillometric and the PTT-CP analysis algorithms. This fusion involves the computation of an unweighted mean of the BP estimates made by the two algorithms. Therefore, if $\mathrm{BP}_{\mathrm{OSC}}$ is an estimate made by the ECG-assisted oscillometric algorithm and $\mathrm{BP}_{\mathrm{PTT}}$ is an estimate made by the PTT-CP analysis algorithm for a particular recording, then the fusion of this information will produce an estimate $\mathrm{BP}_{\mathrm{FUS}} = (\mathrm{BP}_{\mathrm{OSC}} + \mathrm{BP}_{\mathrm{PTT}})/2$, where BP is DP, MAP, and SP. We have chosen the unweighted mean method as a simplistic first approach toward fusion.

### E. Pilot Study

We undertook a pilot study to validate the performance of the InBeam prototype and associated algorithms vis-à-vis the FDA-approved Omron oscillometric BP monitor (HEM-790IT). We analyzed data from ten healthy subjects ($N_T = 10$, Age Range: 24–63 years) out of which six were males ($N_M = 6$, Age Range: 24–44 years) and four were females ($N_F = 4$, Age Range: 24–63 years). To the best of our knowledge, no subjects had any history of cardiovascular or respiratory disease. The University of Ottawa Research Ethics Board authorized the study and written informed consent was obtained from all participants.

A total of 150 concurrent recordings ($R = 150$) were obtained using the InBeam prototype and the Omron BP monitor from the ten subjects ($N_T = 10$). Each subject underwent three data collection sessions on three separate (but not necessarily consecutive) days. Five pairs of recordings were obtained with the InBeam prototype attached to the left arm and the Omron device attached to the right arm during a data collection session or day. Additionally, the wristband of the InBeam prototype was attached to the right wrist of the subjects. A gap of 3 min was provided between each of the five pairs of recordings during a session. The American Heart Association recommends that there be a gap of at least 1 min between two consecutive BP measurements [2]. Since we were measuring BP from both arms five times during a session, a gap of 3 min between each pair of

1. Differentiate the oscillometric signal (solid line, Plot C) with respect to time to obtain its derivative (solid line, Plot D).
2. Find peaks in the derivative of the oscillometric signal: find the maxima of the derivative of the oscillometric signal ordinates (dots, Plot D) that lie between every two consecutive ECG R-peak abscissas (dots, Plot A) and determine their corresponding abscissas.
3. Subtract the abscissas of the ECG R-peaks (dots, Plot A) from the abscissas of the peaks of the derivative of the oscillometric signal (dots, Plot D) to obtain ordinates of the PTT envelope. Find the CP trend line ordinates (dotted line, Plot B) that correspond to the abscissas of the peaks of the derivative of the oscillometric signal (dots, Plot D) to obtain abscissas of the PTT envelope (dotted grey line, Plot F).
4. Subtract the abscissas of the ECG R-peaks (dots, Plot A) from the abscissas of the peaks of the derivative of the oscillometric signal (dots, Plot D) to obtain ordinates of the PTT envelope. Find the CP trend line ordinates (dotted line, Plot B) that correspond to the abscissas of the peaks of the derivative of the oscillometric signal (dots, Plot D) to obtain abscissas of the PTT envelope (dotted grey line, Plot F).
5. Linearly interpolate the PTT envelope with an abscissa (CP) sampling rate of 0.01 mmHg.
6. Smooth the PTT envelope with a cubic smoothing spline function (solid black line, Plot F).
7. Find the maximum value of the ordinates of the smoothed PTT envelope and read off the corresponding abscissa to determine MAP (middle dot, Plot F).
8. Find an ordinate on the PTT envelope (for abscissas less than the MAP abscissa) that is 93 % of the MAP ordinate. Read off the corresponding abscissa of this ordinate to determine DP.
9. Find an ordinate on the PTT envelope (for abscissas greater than the MAP abscissa) that is 95 % of the MAP ordinate. Read off the corresponding abscissa of this ordinate to determine SP.
10. Estimate formula-based mean arterial pressure, $MAP = DP + 1/3 \times (SP - DP)$.

Fig. 4. PTT-CP analysis algorithm.

1. Start session.
2. Start Omron recording (right arm).
3. Start InBeam recording as soon as Omron recording ends (left arm).
4. Wait 3 minutes after InBeam recording ends.
5. Repeat Steps 2-4 four times.
6. End session.
7. Wait for at least 24 hours.
8. Repeat Steps 1-7 two times.

Fig. 5. Data collection protocol for one subject.

measurements was deemed appropriate. In this manner, a total of (three sessions $\times$ five measurements $=$ ) 15 pairs of recordings were obtained from each of the ten subjects, which resulted in a total of (15 recordings $\times$ 10 subjects $=$ ) 150 pairs of recordings for the entire pilot study. See Fig. 5, which summarizes the steps of our data collection protocol for one subject.

All measurements with the InBeam prototype were made during cuff deflation. The brachial cuff was inflated to a pressure of 160 mmHg and then deflated at the rate of 1.5–3.5 mmHg/s until a pressure of 20 mmHg was reached. Following this, CP and ECG signals corresponding to a CP range of 25–155 mmHg were chosen for analysis.

DP, MAP, and SP estimates made by the InBeam prototype were compared with corresponding estimates made by the Omron device. Since the Omron device only outputs DP and SP values, we used the formula-based MAP, MAP $=$ DP $+$ 1/3 $\times$ (SP $-$ DP), for all comparisons and analyses. We employed Bland–Altman plot analysis [37], mean difference (MD $= \sum_{i=1}^{R}((\mathrm{BP}_{\mathrm{InBeam}} - \mathrm{BP}_{\mathrm{Omron}})/R)$, MAD (MAD $= \sum_{i=1}^{R}((|\mathrm{BP}_{\mathrm{InBeam}} - \mathrm{BP}_{\mathrm{Omron}})|/R)$, BHS protocol [33], and Pearson's correlation analysis [38] to compare the performance of the InBeam prototype with that of the Omron device.

## III. Results

The quality and fidelity of all ECG and CP signals ($R = 150$) acquired by the InBeam prototype were satisfactory. The ECG QRS detection algorithm was able to successfully identify ECG $R$-peaks. Following this, our ECG-assisted arterial pulse peak detection method enabled us to readily construct good-quality oscillometric and PTT envelopes.

In Table I, we present a summary of the BP estimates made by the InBeam prototype's fusion algorithm and the Omron device for each subject ($N_T = 10$). Mean and standard deviation (SD) are computed for the 15 BP estimates made by both monitors per subject. The DP, MAP, and SP estimates made by the two monitors are in good agreement for all subjects.

Fig. 6 shows Bland–Altman plots comparing the performance of the InBeam prototype with the Omron BP monitor for all recordings ($R = 150$). The *limits of agreement* (see dotted horizontal lines in Fig. 6) that we use are (bias $\pm$ 1.96 $\times$ SD) for all plots, where bias is the MD between InBeam and Omron measurements. Performances of the ECG-assisted oscillometric analysis algorithm (plots in the first column), the PTT-CP analysis algorithm (plots in the second column), and the fusion algorithm (plots in the third column) are assessed for DP (plots in the first row), MAP (plots in the second row), and SP (plots in the third row). For all plots, majority of the points lie within the *limits of agreement*. Moreover, the bias (see solid horizontal lines in Fig. 6) for all plots is negligible ($\leq \pm 1.7$ mmHg). That is, the BP estimates made by all the three algorithms are in close agreement with those made by the Omron device without being overly biased in any particular direction. We also note that the vertical spread of the points is the least for plots in the third column. This implies that fusing information from the ECG-assisted oscillometric analysis algorithm and the PTT-CP analysis algorithm provides an improvement in BP estimation.

TABLE I
COMPARISON OF BP ESTIMATED BY THE INBEAM FUSION ALGORITHM AND THE OMRON DEVICE FOR EACH SUBJECT

| Subject No. | Age (Yrs.) | Gender | Mean DP ± SD (mmHg) | | Mean MAP ± SD (mmHg) | | Mean SP ± SD (mmHg) | |
|---|---|---|---|---|---|---|---|---|
| | | | Fusion Algorithm | Omron Device | Fusion Algorithm | Omron Device | Fusion Algorithm | Omron Device |
| 1 | 24 | M | 71.20 ± 3.84 | 73.00 ± 4.42 | 88.33 ± 3.98 | 89.67 ± 4.55 | 122.87 ± 8.16 | 123.07 ± 5.93 |
| 2 | 26 | M | 76.33 ± 4.88 | 77.20 ± 3.90 | 89.13 ± 4.45 | 89.47 ± 3.40 | 115.27 ± 5.65 | 114.33 ± 3.89 |
| 3 | 29 | M | 71.47 ± 1.92 | 68.47 ± 3.29 | 83.20 ± 2.68 | 83.20 ± 3.21 | 107.00 ± 5.17 | 112.67 ± 5.43 |
| 4 | 37 | M | 78.87 ± 5.03 | 77.67 ± 4.15 | 92.87 ± 4.88 | 92.67 ± 4.78 | 121.27 ± 5.11 | 122.93 ± 7.54 |
| 5 | 42 | M | 73.13 ± 3.29 | 71.73 ± 3.56 | 82.47 ± 3.07 | 81.60 ± 3.44 | 101.40 ± 4.63 | 101.73 ± 4.20 |
| 6 | 44 | M | 75.87 ± 2.72 | 73.07 ± 2.94 | 86.47 ± 2.72 | 85.40 ± 3.38 | 108.33 ± 3.66 | 110.07 ± 5.71 |
| 7 | 24 | F | 57.53 ± 2.47 | 57.33 ± 2.82 | 66.67 ± 2.55 | 66.00 ± 2.48 | 85.60 ± 3.33 | 83.27 ± 2.79 |
| 8 | 25 | F | 78.27 ± 2.81 | 74.93 ± 2.37 | 88.00 ± 2.45 | 86.40 ± 1.80 | 107.73 ± 3.06 | 109.20 ± 3.38 |
| 9 | 40 | F | 65.20 ± 1.47 | 61.73 ± 2.89 | 74.53 ± 1.25 | 72.67 ± 2.53 | 93.87 ± 3.23 | 94.40 ± 4.79 |
| 10 | 63 | F | 65.00 ± 3.00 | 63.40 ± 3.22 | 74.40 ± 2.53 | 73.93 ± 2.81 | 93.53 ± 2.33 | 94.87 ± 3.60 |

Mean and SD computed for the 15 BP estimates per subject.

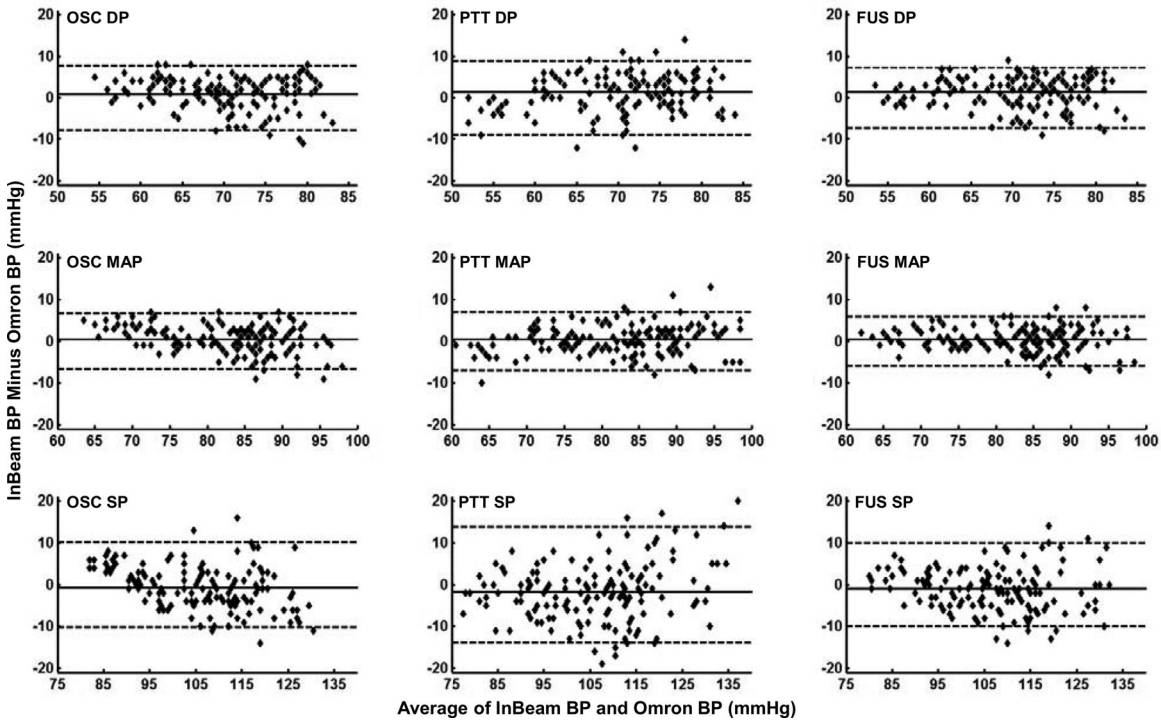


Fig. 6. Bland-Altman plots comparing the performance of the InBeam prototype with the Omron device ($R = 150$).

Table II summarizes the performance of the InBeam prototype vis-à-vis the Omron monitor in terms of MAD and SD of absolute differences for all recordings ($R = 150$). All MADs and SDs are low ($\leq$5.57 mmHg), thus indicating an excellent agreement between the InBeam prototype and the Omron device. For all three BP estimates (DP, MAP, and SP), the fusion algorithm offers improved results as compared to the ECG-assisted oscillometric analysis algorithm and the PTT-CP analysis algorithm alone.

We also computed the MAD and SD of absolute differences of the BP estimates made by the ECG-assisted oscillometric analysis algorithm and PTT-CP analysis algorithm for all recordings

TABLE II
MAD AND SD OF ABSOLUTE DIFFERENCES BETWEEN THE INBEAM PROTOTYPE AND THE OMRON DEVICE

| Algorithm | MAD ± SD (mmHg) | | |
|---|---|---|---|
| | DP | MAP | SP |
| ECG-assisted OSC Analysis | 3.39 ± 2.26 | 2.70 ± 2.00 | 4.27 ± 3.08 |
| PTT-CP Analysis | 3.79 ± 2.74 | 2.81 ± 2.26 | 5.57 ± 4.60 |
| Fusion | 3.31 ± 2.16 | 2.36 ± 1.90 | 4.06 ± 3.25 |

OSC: Oscillometric, $R = 150$.

TABLE III
BHS GRADING: PERCENTAGES OF MADS OF $\leq 5$, $\leq 10$, $\leq 15$ mmHg BETWEEN INBEAM AND OMRON MEASUREMENTS

| Algorithm | Measure | MAD Between InBeam and Omron (mmHg) | | | BHS Grade |
|---|---|---|---|---|---|
| | | ≤ 5 | ≤ 10 | ≤ 15 | |
| ECG-assisted Oscillometric Analysis | DP | 84% | 99% | 100% | A |
| | MAP | 89% | 100% | 100% | A |
| | SP | 71% | 97% | 99% | A |
| PTT-CP Analysis | DP | 75% | 97% | 100% | A |
| | MAP | 89% | 99% | 100% | A |
| | SP | 61% | 83% | 96% | B |
| Fusion | DP | 82% | 100% | 100% | A |
| | MAP | 93% | 100% | 100% | A |
| | SP | 72% | 95% | 100% | A |

$R = 150$.

($R = 150$). The MAD ± SD between the BP estimates made by the two algorithms is 3.11 ± 2.69 mmHg for DP, 2.71 ± 2.40 mmHg for MAP, and 5.40 ± 4.50 mmHg for SP. This indicates a good agreement between the two algorithms for estimating BP.

We present the BHS grading achieved by the InBeam prototype for its comparison with the Omron monitor in Table III. Here, the percentages of MADs that are $\leq$5, $\leq$10, and $\leq$15 mmHg are calculated for all recordings ($R = 150$). Grade A, B, or C is then assigned based on these percentages as per the BHS protocol [33]. The InBeam prototype achieves an overall grade A as per the BHS protocol since the fusion algorithm achieves a grade A for all the three measurements of BP (DP, MAP, and SP).

Table IV shows the comparison of the InBeam prototype with earlier published work that assessed BP based on the PTT-CP analysis. We note that none of the previous four studies integrated or fused the oscillometric analysis with the PTT-CP analysis like the InBeam prototype. Moreover, two of these studies did not provide a validation of their methods. The MD (plus-minus the SD of the differences between BPs measured by the InBeam prototype and the Omron device) and correlation results achieved by the InBeam prototype for DP and SP estimation are comparable to those reported in the earlier studies.

The accuracy of the Omron monitor (HEM-790IT) used for validating the InBeam prototype is ± 3 mmHg [30]. Thus, the accuracy of the InBeam prototype can be calculated using the formula $A_{\mathrm{InBeam}} = \sqrt{SD^2_{\mathrm{InBeam-Omron}} + A^2_{\mathrm{Omron}}}$, where $A_{\mathrm{InBeam}}$ is the statistical accuracy of the BP measured by the InBeam prototype, $\mathrm{SD}_{\mathrm{InBeam-Omron}}$ is the SD of the differences between BPs measured by the InBeam prototype and the Omron device, and $A_{\mathrm{Omron}}$ is the accuracy of the BP measured by the Omron device (±3 mmHg). For the fusion algorithm of the InBeam prototype, $\mathrm{SD}_{\mathrm{InBeam-Omron}}$ for DP is ±3.70 mmHg, MAP is ±2.99 mmHg, and SP is ±5.12 mmHg (Last Row, Columns 8–10, Table IV). Replacing these values in the aforementioned formula results in an accuracy of ±4.76 mmHg for DP, ±4.23 mmHg for MAP, and ±5.93 mmHg for SP for the fusion algorithm of the InBeam prototype. This result confirms that the InBeam prototype achieves a high degree of accuracy and robustness in measuring BP (since $A_{\mathrm{InBeam}}$ is within ±5.93 mmHg).

## IV. CONCLUSION

In this paper, we have introduced a novel method for ECG-assisted BP estimation, whereby an ECG-assisted oscillometric analysis and a PTT-CP analysis have been integrated within the conventional oscillometric BP monitoring paradigm. To accomplish this, we have developed the InBeam prototype and related algorithms that offer two distinct methods of BP estimation—one based on amplitude modulation of oscillometric pulses (ECG-assisted oscillometric analysis) and the other based on temporal modulation of oscillometric pulses (PTT-CP analysis)—and their fusion.

The main finding of this research is that PTT-CP dependence can be utilized for estimating BP even when PTT is computed from arterial pulses that are measured using the same brachial cuff which is also used for occluding the arteries. All previous studies [25]–[28] employed pulse sensors auxiliary to the brachial cuff for studying the PTT-CP dependence. Our method, thus, renders compactness and simplicity to the estimation of BP from the PTT-CP dependence. Furthermore, our ECG-assisted oscillometric analysis method is integrated with the PTT-CP analysis technique. Thus, the fusion of results from these two complementary techniques provides a stable and consistent assessment of BP.

A pilot study analyzing 150 recordings obtained from ten healthy subjects shows high accuracy and robustness of the InBeam prototype vis-à-vis the FDA-approved Omron BP monitor (HEM-790IT). Notably, an improvement in the estimation of all the three measures of BP (DP, MAP, and SP) is achieved when results of the ECG-assisted oscillometric and the PTT-CP analysis algorithms are fused (see Table II and Fig. 6). This highlights the usefulness of integrating complementary BP estimation methods for increasing the robustness and reliability of BP measurements. As per the BHS protocol, the InBeam

TABLE IV
COMPARISON OF THE INBEAM PROTOTYPE WITH EARLIER PUBLISHED WORK

| Authors | Subject Type | No. of Subjects ($N_T$) | Health Status | No. of Recordings (R) | BP Estimation Method | Validation Method | MD ± SD (mmHg) | | | Correlation | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | DP | MAP | SP | DP | MAP | SP |
| Geddes et al. [25] | Dogs | NS | Normo-Hypertensive Hypotensive Anesthetized | NS | PTT-CP Analysis | NS | NS | NS | NS | NS | NS | NS |
| Kerola et al. [28] | Adult Humans | 28 | NS | NS | PTT-CP Analysis | NS | NS | NS | NS | NS | NS | NS |
| Sharir et al. [26] | Adult Humans | 57 | 21 Healthy 36 CAD | NS | PTT-CP Analysis | Invasive | NS | NS | NS | 88% | NS | 97% |
| Sorvoja et al. [27] | Adult Humans | 16 | Healthy | 121 | PTT-CP Analysis | Invasive | 0.10 ± 7.30 | NS | -7.10 ± 8.30 | NS | NS | NS |
| Ahmad et al. (Pilot Study) | Adult Humans | 10 | Healthy | 150 | Integrated ECG-assisted OSC & PTT-CP Analysis | Omron HEM-790IT | 1.43 ± 3.70 | 0.51 ± 2.99 | -0.97 ± 5.12 | 87% | 94% | 92% |

NS: Not Specified, CAD: Coronary Artery Disease, OSC: Oscillometric, All Correlations: p<0.0001.

prototype achieves a grade A for DP, MAP, and SP estimation (see Table III).

The FDA-approved Omron BP monitor (HEM-790IT) that we used for validating the InBeam prototype is a precision medical device. This monitor has passed rigorous clinical testing according to protocols set forth by the European Society of Hypertension, Association for the Advancement of Medical Instruments, and BHS [31], [32]. Therefore, for this pilot investigation, the successful validation of the InBeam prototype against the Omron monitor is sufficient to prove the significance and efficacy of the proposed method and algorithms. Future work will involve converting the InBeam prototype into a standalone industrial prototype and undertaking clinical testing on patients, whereby the device will be compared against nurse-recorded auscultatory measurements, and if possible, against invasive measurements.

The shapes of the oscillometric and PTT envelopes that we obtained are somewhat similar in that they both attain a maximum value when CP is equal to MAP and decrease for CPs that are lower or higher than MAP (see Plots E and F, Fig. 2). When CP is equal to MAP, the resultant pressure on the arterial wall is close to zero. Thus, amplitudes of arterial pulsations are highest at this stage and die out elsewhere. This characterizes the shape of the oscillometric envelope. Moreover, at this stage, when CP or $P_{\mathrm{CP}}$ is equal to the internal pressure $P_0$ or MAP, PTT attains its maximum value [as per (2)] and diminishes elsewhere. This characterizes the shape of the PTT envelope.

One of the challenges that we faced in this project was that we had to manually adjust the pressure release valve of the InBeam prototype before each recording session to obtain a cuff deflation rate of 1.5–3.5 mmHg/s. Since the cuff deflation mechanism of the InBeam prototype is not computer controlled, the screw on the pressure release valve had to be manually adjusted owing to different arm sizes and arterial properties of the subjects. Before the start of each session (which comprised five measurements), the manual adjustment of the cuff deflation rate took about 2 min after which the session proceeded as per the protocol (see Fig. 5). Despite the challenge of having to adjust the cuff deflation rate manually before each session, we were able to get good quality oscillometric signals ($R = 150$) with a consistent deflation rate of 1.5–3.5 mmHg/s for the entire pilot study. We are currently working on developing a computer-controlled cuff deflation mechanism for the next version of the InBeam prototype.

There are many potential benefits of integrating the ECG-assisted oscillometric and PTT-CP analysis into the standard oscillometric BP estimation technique. For example, for obese subjects, the amplitudes of the measured arterial pulses are weak, which may render the oscillometric BP estimation method prone to errors [6], [7]. Under such conditions, the PTT-CP analysis is likely to produce better results since it is based on temporal modulation of the pulses. Moreover, the difference in BP estimated by the ECG-assisted oscillometric and PTT-CP analysis algorithms may be utilized for providing an index for the reliability of a particular measurement.

## REFERENCES

[1] R. E. Klabunde, *Cardiovascular Physiology Concepts*. Baltimore, MD: Williams & Wilkins, 2005.

[2] T. G. Pickering, J. E. Hall, L. J. Appel, B. E. Falkner, J. Graves, M. N. Hill, D. W. Jones, T. Kurtz, S. G. Sheps, and E. J. Roccella, "Recommendations for blood pressure measurement in humans and experimental animals—Part 1: Blood pressure measurement in humans: A statement for professionals from the subcommittee of professional and public education of the American Heart Association Council on high blood pressure research," *Hypertension*, vol. 45, pp. 142–161, 2005.

[3] P. D. Baker, D. R. Westenskow, and K. Kück, "Theoretical analysis of non-invasive oscillometric maximum amplitude algorithm for estimating mean blood pressure," *Med. Biol. Eng. Comput.*, vol. 35, pp. 271–278, 1997.

[4] Z. M. Anastas, E. Jimerson, and S. Garolis, "Comparison of noninvasive blood pressure measurements in patients with atrial fibrillation," *J. Cardiovasc. Nurs.*, vol. 23, pp. 519–524, 2008.

[5] B. Jani, C. J. Bulpitt, and C. Rajkumar, "Blood pressure measurement in patients with rate controlled atrial fibrillation using mercury sphygmomanometer and Omron HEM-750CP device in the clinic setting," *J. Human Hypertens*, vol. 20, pp. 543–545, 2006.

[6] E. O'Brien, "A century of confusion: which bladder for accurate blood pressure measurement?" *J. Human Hypertens.*, vol. 10, pp. 565–572, 1996.

[7] M. T. Guagnano, V. P. Palitti, R. Murri, L. Marchione, D. Merlitti, and S. Sensi, "Many factors can affect the prevalence of hypertension in obese

patients: Role of cuff size and type of obesity," *Panminerva Med*, vol. 40, pp. 22–27, 1998.
[8] G. Beevers, G. Y. H. Lip, and E. O'Brien, "ABC of hypertension: Blood pressure measurement—Part I: Sphygmomanometry: Factors common to all techniques," *Brit. Med. J.*, vol. 322, pp. 981–985, 2001.
[9] C. Sala, E. Santin, M. Rescaldani, C. Cuspidi, and F. Magrini, "What is the accuracy of clinic blood pressure measurement?" *Amer. J. Hypertension*, vol. 18, pp. 244–248, 2005.
[10] R. A. Walloch, "Automatic blood pressure monitor employing artifact rejection method and apparatus," U.S. Patent # 5 337 750, 1994.
[11] "Noninvasive Blood Pressure Measurement and Motion Artifact: A Comparative Study," Revision Labs Inc., Beaverton, OR, 1998.
[12] R. P. Smith, J. Argod, J.-L. Pépin, and P. A. Lévy, "Pulse transit time: An appraisal of potential clinical applications," *Thorax*, vol. 54, pp. 452–457, 1999.
[13] J. Y. A. Foo and C. S. Lim, "Pulse transit time as an indirect marker for variations in cardiovascular related reactivity," *Technol. Health Care*, vol. 14, pp. 97–108, 2006.
[14] W. W. Nicholas and M. F. O'Rourke, *McDonald's Blood Flow in Arteries: Theoretical, Experimental and Clinical Principles*, 4th ed. New York: Oxford Univ. Press, 1998.
[15] E. R. Nye, "The effect of blood pressure alteration on the pulse wave velocity," *Brit. Heart J.*, vol. 26, pp. 261–265, 1964.
[16] Y. Chen, L. Li, C. Hershler, and R. P. Dill, "Continuous non-invasive blood pressure monitoring method and apparatus," U.S. Patent 6 599 251B2, Jul. 29, 2003.
[17] K. Meigas, J. Lass, D. Karai, R. Karai, and J. Kaik, "Pulse wave velocity in continuous blood pressure measurements," *IFMBE Proc.*, vol. 14, pp. 626–629, 2007.
[18] Y. Kim, "Automatic blood pressure measuring instrument and method thereof, " U.S. Patent 7 226 418B2, Jun. 5, 2007.
[19] S. S. Najjar, A. Scuteri, V. Shetty, J. G. Wright, D. C. Muller, J. L. Fleg, H. P. Spurgeon, L. Ferrucci, and E. G. Lakatta, "Pulse wave velocity is an independent predictor of the longitudinal increase in systolic blood pressure and of incident hypertension in the Baltimore longitudinal study of aging," *J. Amer. Coll. Cardiol.*, vol. 51, pp. 1377–1383, 2008.
[20] Y. Yoon, J. H. Cho, and G. Yoon, "Non-constrained blood pressure monitoring using ECG and PPG for personal healthcare," *J. Med. Syst.*, vol. 33, pp. 261–266, 2009.
[21] K. Ha, Y. Park, and J. Lee, "Apparatus and method for measuring blood pressure, " U.S. Patent # 20 100 049 059, 2010.
[22] J. D. Lane, L. Greenstadt, D. Shapiro, and R. Rubinstein, "Pulse transit time and blood pressure: An intensive analysis," *Psychophysiology*, vol. 20, pp. 45–49, 1983.
[23] Y. Sawada and K. Yamakoshi, "A correlation analysis between pulse transit time and instantaneous blood pressure measured indirectly by the vascular unloading method," *Biol. Psychol.*, vol. 21, pp. 1–9, 1985.
[24] R. A. Payne, C. N. Symeonides, D. J. Webb, and S. R. J. Maxwell, "Pulse transit time measured from the ECG: An unreliable marker of beat-to-beat blood pressure," *J. Appl. Physiol.*, vol. 100, pp. 136–141, 2006.
[25] L. A. Geddes, M. Voelz, S. James, and D. Reiner, "Pulse arrival time as a method of obtaining systolic and diastolic blood pressure indirectly," *Technical Note, Med. Biol. Eng. Comput.*, vol. 19, pp. 671–672, 1981.
[26] T. Sharir, A. Marmor, C. T. Ting, J. W. Chen, C. P. Liu, M. S. Chang, F. C. Yin, and D. A. Kass, "Validation of a method for noninvasive measurement of central arterial pressure," *Hypertension*, vol. 21, pp. 74–82, 1993.
[27] H. Sorvoja, R. Myllylä, P. Kärjä-Koskenkari, J. Koskenkari, M. Lilja, and Y. A. Kesäniemi, "Accuracy comparison of oscillometric and electronic palpation blood pressure measuring methods using intra-arterial method as a reference," *Molecular Quantum Acoust.*, vol. 26, pp. 235–260, 2005.
[28] J. Kerola, V. Kontra, and R. Sepponen, "Non-invasive blood pressure data acquisition employing pulse transit time detection," in *Proc. 18th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, vol. 3, Amsterdam, The Netherlands, 1996, pp. 1308–1309.
[29] S. Ahmad, S. Chen, K. Soueidan, I. Batkin, M. Bolic, H. Dajani, and V. Groza, "A prototype of an integrated blood pressure and electrocardiogram device for multi-parameter physiologic monitoring," in *Proc. IEEE Instrum. Meas. Technol. Conf.*, Austin, TX, 2010, pp. 1244–1249.
[30] Omron® Instruction Manual, "Automatic blood pressure monitor with ComFit™ cuff: Model HEM-790IT," Omron Healthcare Inc., Bannockburn, IL, 2006.
[31] R. N. Feghali, J. A. Topouchaian, B. M. Pannier, H. A El Assaad, and R. G. Asmar, "Validation of the Omron M7 (HEM-780-E) blood pressure measuring device in a population requiring large cuff use according to the International Protocol of the European Society of Hypertension," *Blood Pressure Monitoring*, vol. 12, pp. 173–178, 2007.
[32] A. Coleman, S. Steel, P. Freeman, A. de Greeff, and A. Shennan, "Validation of the Omron M7 (HEM-780-E) oscillometric blood pressure monitoring device according to the British Hypertension Society protocol," *Blood Pressure Monitoring*, vol. 13, pp. 49–54, 2008.
[33] L. A. Bortolotto, O. Henry, O. Hanon, P. Sikias, J. J. Mourad, and X. Girerd, "Validation of two devices for self-measurement of blood pressure by elderly patients according to the revised British Hypertension Society Protocol: The Omron HEM-722C and HEM-735C," *Blood Press Monitoring*, vol. 4, pp. 21–25, 1998.
[34] QRS onset detector. (Aug. 2010). Harvard-MIT Health Sci Technology [Online]. Available: http://www.mit.edu/~gari/CODE/ECGtools/ecgBag/sqrs.m
[35] Single channel QRS detector. (Aug. 2010). PhysioNET [Online]. Available: http://www.physionet.org/physiotools/wfdb/app/sqrs.c.
[36] P. Dadelszen, M. P. Ornstein, S. B. Bull, A. G. Logan, G. Koren, and L. A. Magee, "Fall in mean arterial pressure and fetal growth restriction in pregnancy hypertension: A meta-analysis," *Lancet*, vol. 355, no. 9198, pp. 87–92, 2000.
[37] S. K. Hanneman, "Design, analysis, and interpretation of method-comparison studies," *AACN Adv. Critical Care*, vol. 19, pp. 223–234, 2008.
[38] J. L. Rodgers and W. A. Nicewander, "Thirteen ways to look at the correlation coefficient," *The Amer. Statistician*, vol. 42, pp. 59–66, 1988.

**Saif Ahmad** received the B.Sc. degree in electrical engineering from Aligarh Muslim University, Aligarh, India, in 1996, the M.Sc. degree in computer science from the University of Birmingham, Birmingham, U.K., in 2001, and the Ph.D. degree in computer science from the University of Surrey, Guildford, U.K., in 2007.

He is currently a Research Associate in the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada. Prior to this, he was a Postdoctoral Fellow in the Divisions of Thoracic Surgery and Critical Care Medicine, Ottawa General Hospital, Ottawa. He has over three years of industrial experience related to high-voltage engineering, electrical power generation and distribution, and electrical machines at Tata Chemicals Ltd., headquartered at Mumbai, India. He is the author or coauthor of more than 14 papers published in peer reviewed journals and conference proceedings. In 2009, his work on heart rate variability analysis for the diagnosis, prognosis, and prediction of sepsis was published in PLoS One and Critical Care. This work was also accorded prominent coverage by the Ottawa Citizen. He has served as a Reviewer for several IEEE and medical journals as well as conference proceedings. His major research interests include medical device development, biomedical signal processing, and financial time series analysis.

**Silu Chen** received the B.Sc. degree in electrical engineering and the M.Sc. degree in electrical and computer engineering from the University of Ottawa, Ottawa, ON, Canada, in 2008 and 2010, respectively.

He is currently a Digital Hardware System Designer at Research in Motion, Waterloo, ON, Canada. He has more than two years of experience in the telecommunications industry. He has published over five journal and conference proceedings papers. His major research interests include signal processing and biomedical engineering.

**Karen Soueidan** (M'08) received the B.Sc. degree in computer engineering and the MA.Sc. degree in biomedical engineering from the University of Ottawa, Ottawa, ON, Canada, in 2008 and 2010, respectively.

She is currently a Research Assistant at the University of Ottawa Heart Institute, Ottawa, where she is involved in the research on cardiac nuclear imaging. Her research has led to more than four publications focusing on blood pressure measurement and devices.

**Izmail Batkin** received the M.S. and Ph.D. degrees in theoretical physics from the Voronezh State University, Voronezh, Russia, in 1965 and 1969, respectively, and the Dr.Sci. degree in nuclear physics from the Leningrad State University, Saint Petersburg, Russia, in 1982.

He is currently a Research Consultant in the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada, and at Ottawa General Hospital, Ottawa. He is also the Chief Scientist at Biopeak Corporation, Ottawa, ON, Canada. Prior to this, he was a Professor at the Voronezh State University, and an Adjunct Professor at Carleton University, Ottawa. Over the years, his research has focused on noninvasive monitoring of physiological parameters. He has been involved in the successful development and testing of a new generation of wearable physiological electrodes and monitors for the home and clinical environments. He has obtained one patent and published more than 150 refereed papers—many in top notch journals such as *Physical Review*, the *Journal of Physics*, and the *Soviet Journal of Nuclear Physics*. His major research interests include theoretical and nuclear physics, and medical physics.

**Miodrag Bolic** (M'04–SM'08) received the B.Sc. and M.Sc. degrees in electrical engineering from the University of Belgrade, Belgrade, Serbia, in 1996 and 2001, respectively, and the Ph.D. degree in electrical engineering from Stony Brook University, Stony Brook, NY, in 2004.

He is currently an Associate Professor in the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada. He has more than seven years of industrial experience related to embedded system design and signal processing. He is the Director of the Radio Frequency Identification Systems Laboratory and Computer Architecture Research Group at the University of Ottawa. He is the author or coauthor of more than 60 journal and conference papers. His research interests include computer architectures, hardware accelerators, signal processing for biomedical applications, and radio frequency identification.

**Hilmi Dajani** (M'07–SM'11) received the B.Eng. degree in electrical engineering from McMaster University, Hamilton, ON, Canada, in 1987, and the M.Sc. and Ph.D. (collaborative program in biomedical engineering) degrees in electrical and computer engineering from the University of Toronto, Toronto, ON, in 1991 and 2004, respectively.

He is currently an Assistant Professor in the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON. He has several years of experience in implementing technical projects in a hospital setting and in the biomedical technology industry. He has also conducted research on auditory-inspired speech processing, speech-evoked potentials, and speech production with modified auditory feedback. His research interests include the development of new methods for the analysis of cardio-respiratory function, and the development of instrumentation for the assessment and treatment of speech and hearing impairments.

**Voicu Groza** (M'97–SM'02) received the Dipl.Eng. degree in computer engineering and the Dr.Eng. degree in electrical engineering from the Polytechnic Institute of Timisoara, Timisoara, Romania, in 1972 and 1985, respectively.

He was a Professor at the Polytechnic University of Timisoara. In 1997, he joined the School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada. He is the author or coauthor of more than 150 technical papers. His research interests include biomedical instrumentation and measurement, and reconfigurable computers.

Dr. Groza has served as a Conference or Technical Program Chair at several major international events such as the IEEE International Workshop on Medical Measurement and Applications (MeMeA: 2008–2010), the IEEE International Conference on Instrumentation and Measurement (IMTC: 2005), and the IEEE Canadian Conference on Electrical and Computer Engineering (CCECE: 2006). He is currently the Chair of the IEEE Working Group on Standard for Objective Measurement of Systemic Arterial Blood Pressure in Humans.