BioWatch: A Non-invasive Wrist-based Blood Pressure Monitor that Incorporates Training Techniques for Posture and Subject Variability

Simi Susan Thomas, Viswam Nathan, Chengzhi Zong, Karthikeyan Soundarapandian, Xiangrong Shi, Roozbeh Jafari, *IEEE Senior Member*

***Abstract*— Noninvasive continuous blood pressure (BP) monitoring is not yet practically available for daily use. Challenges include making the system easily wearable, reducing noise level and improving accuracy. Variations in each person's physical characteristics, as well as the possibility of different postures, increases the complexity of continuous BP monitoring, especially outside the hospital. This work attempts to provide an easily wearable solution and proposes training to specific posture and individual for further improving accuracy. The wrist watch based system we developed can measure electrocardiogram (ECG) and photoplethysmogram (PPG). From these two signals we measure pulse transit time (PTT) through which we can obtain systolic and diastolic blood pressure through regression techniques. In this work, we investigate various functions to perform the training to obtain blood pressure. We validate measurements on different postures and subjects, and show the value of training the device to each posture and each subject. We observed that the average RMSE between the measured actual systolic BP and calculated systolic BP is between 7.83mmHg to 9.37mmHg across 11 subjects. The corresponding range of error for diastolic BP is 5.77 to 6.90mmHg. The system can also automatically detect the arm position of the user using an accelerometer with an average accuracy of 98%, to make sure that the sensor is kept at the proper height. This system, called BioWatch, can potentially be a unified solution for heart rate, SPO2 and continuous BP monitoring.**

***Index Terms*— Blood Pressure, Electrocardiogram, Photoplethysmogram, Pulse transit time, Wrist-based physiological monitoring.**

This work was supported in part by the National Science Foundation, under grant CNS-1150079, Texas Instruments Inc., and the Semiconductor Research Corporation, task #1836.103 through the Texas Analog Center of Excellence (TxACE). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding organizations.

Simi Susan Thomas and Chengzhi Zong are with the Electrical Engineering department at the University of Texas at Dallas, Richardson, Texas, 75080, USA. (e-mails: {sxt129030,cxz121430}@utdallas.edu)

Karthikeyan Soundarapandian is with Texas Instruments Incorporated, Dallas, Texas, 75243, USA. (e-mail: skarthi@ti.com).

Xiangrong Shi is with Physiology and Anatomy department of University of North Texas Health Science Center, Fort Worth, Texas, 76107, USA. (e-mail: Xiangrong.Shi@unthsc.edu)

Viswam Nathan and Roozbeh Jafari are with the Computer Science and Engineering department at Texas A&M University, College Station, Texas, 77843, USA. (e-mails: {viswamnathan,rjafari}@tamu.edu)

I. INTRODUCTION

MAINTAINING a healthy lifestyle is a challenge in today's world. With a diet filled with fast foods and a hectic work culture, it takes extra efforts to be healthy. According to statistics from Centers for Disease Control and Prevention (CDC), heart disease is the leading cause of death for both men and women. According to CDC about 600,000 people die of heart disease in the United States every year which is 1 in every 4 deaths [1]. One of the most important and easiest ways to keep track of the heart's health is by monitoring blood pressure (BP). With the increased interest in personal health monitoring products and development of new wearable sensors, a continuous non-invasive wearable BP device would be a great asset for a health enthusiast or someone who is diagnosed with heart related ailments. Even though different studies have proposed noninvasive solutions like measuring BP from the pulse transit time (PTT) [2] or from the radial artery [3][4], an easily wearable product for this purpose is still not available in the market. Such a device should not only provide accurate and reliable readings of BP but also be easy to use in a convenient form factor that does not unduly burden the user for daily use. Gearing towards this goal, we dedicated our effort to develop a non-invasive wearable BP monitoring device using PTT.

Over the years researchers have observed that PTT correlates well with systolic BP (SBP) [5][6][7][8]. Since PTT can be calculated using electrocardiogram (ECG) and photoplethysmogram (PPG) [9], it can be leveraged to obtain a continuous and non-invasive measurement of SBP. Diastolic BP (DBP) on the other hand has been shown in previous studies, such as [5], to not correlate as well with PTT. This was also confirmed by our own experiments described later in this text. However, we can get around this restriction by using pulse pressure (PP) instead. PP is simply the difference between SBP and DBP and it has been shown to correlate better with PTT [8][10]. So once we estimate SBP and PP through regression techniques, we can obtain DBP using simple subtraction.

In order to measure PTT we need the ECG and PPG; in many of the previous studies the modules which measured these two signals were separate. This arrangement results in the challenge of proper synchronization and these systems were not independently wearable [11][12]. Among the studies which tried to introduce wearable BP measurement devices, the wearable solution in [13] is not convenient enough because of its wired connection extension to the other arm, which will be uncomfortable if worn all day and the study by Kim et al [14] did not provide a clear validation on the measured BP. In this paper, we present BioWatch, a wearable device in the form of a wrist watch that can monitor the user's BP non-invasively. BioWatch can also monitor heart rate using either ECG or PPG and measure blood oxygenation by easily replacing the PPG sensors with a different set. The system uses Bluetooth for wireless transmission which makes BioWatch an easily wearable device. Fig. 1 shows BioWatch worn by a person. The user wears it on the left hand and touches the ECG electrode with the right hand to complete the electrical connection for the ECG.

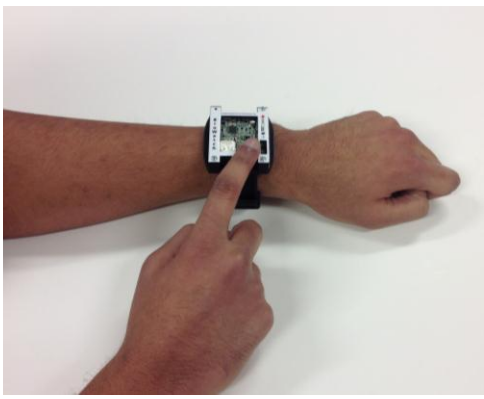

Fig. 1: Biowatch with two electrodes underneath the watch making contact with the left arm and the top electrode making contact with the right arm via a finger touch.

While this study focuses on the relationship between PTT and BP, it must be noted that there are studies which show that there are other PPG characteristics which also correlate with BP. In [10] it is shown that the RSD (the time ratio of systole to diastole), RtArea (area ratio of systole to diastole), TmBB (time span of PPG cycle) and TmCA (diastolic duration) are also correlated with BP. According to this paper using more than one of these indices will improve the BP estimation. However, the PPG data in the above mentioned work is collected at the fingertip while the PPG collected in our experiments is from the wrist. PPG waveforms acquired from different positions of body can be different in appearance, which in turn can affect the recognition and validity of certain features. Therefore, more extensive analysis is required in order to fully explore the possibilities of using alternate features with a wrist-based PPG. The scope of this manuscript is focused on wearable system design and development of techniques to translate PTT to BP.

The human body is complex and there are many physiological factors, such as physical characteristics of blood vessels, which influence BP and PTT. Some studies show that factors like mood or mental stress [15], race [16] and posture can influence BP or PTT [17][18][19]. The effect of these varies from individual to individual and can change with age or health conditions in each individual. Because of these different and complex factors, coming up with a single solution for accurately calculating BP from PTT is extremely difficult without controlling some of these factors. Calibration is one of the viable methods addressing this issue.

A simple one-point calibration which uses a fixed BP shift to make up the bias of an empirical formula is proposed in [20]. Some other empirical formula based works have investigated adaptive kalman filter (AKF) for continuous calibration [21] and Hilbert-Huang Transformation (HHT) for better PTT generation [22]. Apart from the empirical formula based method, linear regression is also applied to derive the relationship between BP and PTT [23, 24]. However, firstly, there is no clear justification behind the assumption of a linear relationship for PTT-based BP estimation. Secondly, most PTT-BP relationship studies are done while assuming only one posture. Finally, one of the most important reasons for the demand of continuous calibration in empirical formula based methods is the lack of the ability to track the height difference between heart and measurement position.

The main contributions of our work are as follows:

- Multiple closed-form regression relationships between BP and PTT are investigated.
- Analysis of the effects of inter-subject and posture variations on the BP estimation validating the need of training for each individual and each posture.
- Method to detect height difference between the heart and the point of measurement is designed to provide feedback to the user in order to correct the arm position in real time.

II. Background

Every time the heart beats, there is a rush of blood from the heart to all parts of the body. The speed of this movement is directly proportional to the BP. So the time taken for the blood to travel from heart to any specific location in the human body is inversely proportional to BP and this corresponds to the PTT. The speed of this travel corresponds to the pulse wave velocity (PWV). By measuring PTT non-invasively and continuously we can then estimate SBP and DBP.

A. *Definition of PTT*

PTT can be defined as the time between the ECG 'R peak' and the corresponding maximum inclination in the PPG [9]. This is illustrated in Figure 2, which shows filtered ECG and PPG waveforms from BioWatch. PTT divided by the distance of travel, which is approximately the arm length in our case, gives us the PWV. The PTT measured here also includes the PEP, which is the interval between the onset of the QRS complex in ECG and actual cardiac ejection of the blood from the heart. Ideally, we would have to remove PEP from PTT to get the true PWV.

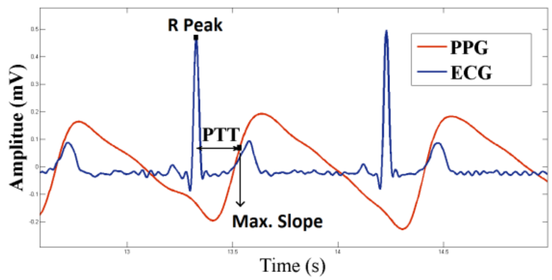

Fig. 2: PTT obtained from filtered ECG & PPG collected through BioWatch.

According to [25] PEP varies with different postures. Since our method calibrates and trains the PTT-BP equation to each individual and posture, this should eliminate the effect of PEP on the resulting BP. Keeping this in mind we decided not to take the extra burden to measure PEP separately.

III. Hardware Description

Our first goal was to integrate both ECG and PPG measuring devices into one unit in a wrist watch form factor. The platform used for BioWatch is designed by our lab, the Embedded Signal Processing Lab (ESP), in partnership with Texas Instruments (TI). In an earlier project called Health Hub for TI, we developed a wrist watch based Heart Rate and SPO2 monitor. In that system we used a flat PPG sensor with both IR and Red LEDs. Taking this design as the base we added the ECG circuitry. To get the ECG signal across the heart we need two differential electrodes making contact with the body on opposite sides of the heart. A third bias electrode is also required for this system to bias the signals to within proper operating range for the amplifiers. The positive differential electrode and the bias electrode are placed underneath the watch where they will make contact with the left arm and the negative differential electrode is placed on top so that the user can touch it with the right hand.

BioWatch comes with two analog front ends (AFE): the TI ADS1292 for acquiring ECG signal and the TI AFE4400 for reading PPG. The board also contains a nine-axis (Accelerometer + Gyro + Magnetometer) MEMS inertial sensor (MPU-9150 from InvenSense, Inc), which allows to sense body movements and detect posture. More details of the hardware and its operation are available in our earlier papers [26][27].

IV. Methods

As a first step to validate our hardware we verified the correlation between the measured PTT and SBP, as well as between PTT and PP. We then looked into how SBP and PTT changes for different postures on different individuals. Conclusions from these steps led to the training of PTT to BP equations for each individual and for each posture. This training was done to generate fitted equations for SBP and DBP. The results were analyzed to quantify how much the specific posture and subject training affected the resulting BP calculation. Finally, the accelerometer data available from BioWatch was used to develop arm position detection techniques.

A. *Measuring reference BP*

Using a reference device, the Colin Continuous Blood Pressure Monitor CBM-7000, arterial blood pressure (ABP) is measured continuously from the radial artery. More details of this reference device are provided in Section V-A. Fig. 3 shows the beat to beat ABP. In a window of one heartbeat, the peak of the measured signal corresponds to the SBP, whereas the valley corresponds to the DBP. The difference between these corresponds to the PP. We use this to get beat-to-beat reference measurements for BP.

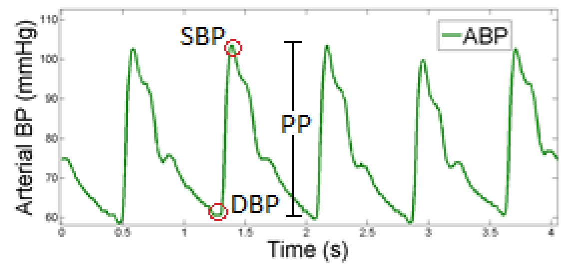

Fig. 3: ABP collected from Radial Artery

B. *Translating PTT to BP*

We know PTT is correlated with SBP and PP, and the exact relationship is a function of various factors such as age, height, thickness of blood vessels and so on. Instead of identifying all the factors and coming up with a fixed relationship, we train equations using curve fitting and regression techniques to capture this relationship in a training data set. This method also allows us the flexibility to easily generate different equations for different postures, which we will show to be important.

The PTT from BioWatch is measured along with the ABP from a reference device which gives us the ground truth. PTT can change depending on individual arm lengths but PWV can give a better stable value across different individuals having the same BP and will also help in comparing results across different individuals. So before beginning the curve fitting process, the PTT is first transformed to PWV as defined below:

$$PWV = \frac{d}{PTT} \tag{1}$$

Here d is the distance from heart to the wrist and is calculated as 50% of the height of the individual [20]. This measure is also supported by studies such as [28] where a high correlation between arm-span and body height is shown.

We attempted five different types of function formats for the fitting function that was to be trained. The equations were of varying complexity and the idea was to compare their performance in capturing the relationship between PWV and SBP (or PP) and see which equation type would provide the optimum balance between complexity and accuracy. One common fitting function is polynomial regression as described below:

$$y = a_0 + a_1 \times x + a_2 \times x^2 + \ldots\ldots + a_k \times x^k \quad (2)$$

Here, k is the order of the fitting function, x is the PWV and y is either the SBP or PP, depending on which reference was used. In this work, we attempted only polynomial equations of orders 1 and 2.

In [9], BP is calculated as 70% of the total pressure drop ΔBP in the body, where ΔBP is calculated as shown below.

$$\Delta BP = \frac{1}{2}\rho \frac{d^2}{PTT^2} + \rho g h \quad (3)$$

Here ρ is the density of the blood, d is the distance from heart to the wrist, g is the gravity of earth and h is the height difference between the two sites: the heart and the wrist. We trained a generalized equation based on this BP model as defined below:

$$y = ax^2 + b \quad (4)$$

where x is the PWV, y is the SBP (or PP) measure and a,b are constants which are determined by the curve fitting process. In addition, we also tested two exponential equation formats. Table I summarizes all the equations used to train the fitting function. Parameters a, b & c are determined after the training. Evidently, more complex equations would be able to fit a given training data set better, but there are two factors that would favor opting for a simpler equation. Firstly, the system is expected to be a real-time implementation on a wearable device with a microcontroller, thus restricting its ability to perform complex computations. Secondly, simpler equations would be less susceptible to over-fitting to a particular training data set and proving less effective for the remaining testing data. We also primarily considered polynomial and exponential equations since many previous works like [9] and [20] used similar models.

Table I : Different fitting functions used for training

Fitting Eq. No:	Equations
1	$y = ax + b$
2	$y = ax^2 + bx + c$
3	$y = ax^2 + b$
4	$y = ax^b + c$
5	$y = ae^{bx}$

In order to test and compare the performance of the trained equations, the data set is divided into 10 segments and 9 were used for training. The effectiveness of each equation is tested on the untrained segment. A 10-fold cross validation is done to compute the root mean square error (RMSE) between the calculated SBP and the actual measured SBP as measured by the reference device. The process is also repeated for DBP; the trained estimate of PP is subtracted from the corresponding trained estimate of SBP to get the calculated DBP which is then compared to the reference DBP. This procedure is repeated for all 3 postures on all subjects

C. Position Detection

While measuring the PTT, users are encouraged to keep their arm with BioWatch, across the chest at position C as shown in Fig. 4 and this is the position used for training the equations. Changing this position every time the user measures the BP can lead to less accurate results. Studies show that differences in the height of the sensor position relative to the heart can change the PTT values [29]. We verified this phenomenon using a simple test: we asked one subject to keep the arm in 5 different positions, as shown in Figure 4, and measured the PTT and resulting BP measure for each position. This test was conducted over a span of 2 to 3 minutes and the results detailing the BP variation are shown in Table IX in Section VI-E. After this experiment we heuristically defined a range of ±2cm as the acceptable arm position deviation from the training position for results to remain consistent. A wider range means the BP measurement will be less reliable and a shorter range can make proper positioning of the arm difficult for the user.

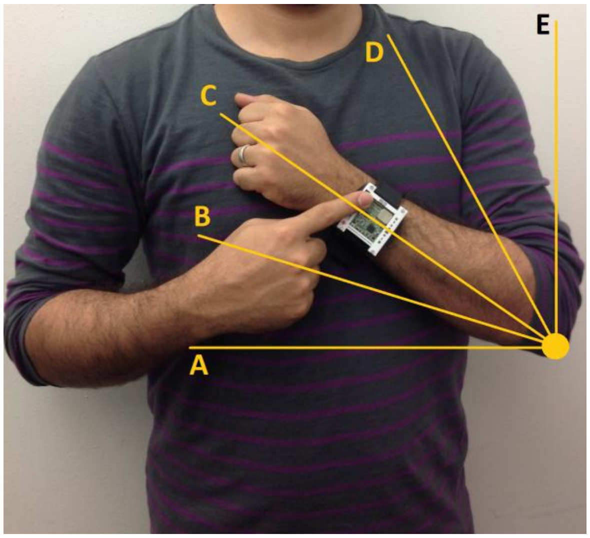

Fig. 4: Different arm positions with BioWatch. In this case position C is the position during the training.

We wanted to correlate this range of acceptable arm position with a range of values on the accelerometer. The 3-axis acceleration is captured by the accelerometer on the BioWatch and is sent to the PC during the data collection. Since the BP is measured when the subject is stationary (*e.g.* standing, sitting and supine), the accelerometer only measures the effect of gravity on the three axes. In this work, the accelerometer orientation and position are assumed to be fixed as the user is expected to wear the watch in a relatively similar fashion each time. This meant that arm position changes along the plane as shown in Figure 4 were captured best by the y-axis readings of the accelerometer, denoted as g_y, and this is effectively the projection of gravity along the y-axis. To define the acceptable g_y range we used the lower arm length (defined as the length from the elbow to the wrist where the subject has worn the BioWatch), g_y value during training, the gravity of earth g and the previously defined range of acceptable sensor height change (±2cm). In Fig. 5, CA is the arm position during training, CF is the upper limit of the arm position and CD is the lower limit. In other words, arcs FA and AD are 2cm long in our case.

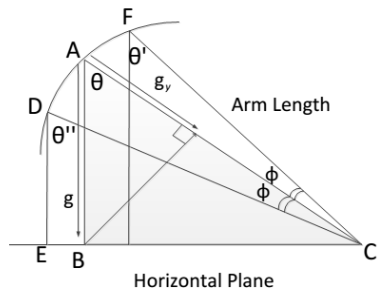

Fig. 5: Measuring g_y range

We can then see that:

$$\theta = \arccos\left(\frac{g_y}{g}\right) \tag{5}$$

where θ is the angle made by the arm to the axis of gravity. The angle ϕ corresponding to each arc of 2cm is computed as follows:

$$\phi = \frac{AF \times 360}{2\pi \times AC} \tag{6}$$

It is then trivial to obtain all the other relevant angles. Finally the upper g_y limit can be computed as follows:

$$g_y' = g \times \cos\theta' \tag{7}$$

Here $g_{y'}$ is the projection of gravity on the y-axis when the arm is placed at the upper limit of the sensor height change and θ' is the corresponding angle made by the arm to the axis of gravity. Similarly the lower limit of g_y is also computed. Here we assume that the position of the elbow is relatively fixed.

Using this method we find the acceptable range of g_y for each individual during the training phase. This range can then be used to indicate to the user whether they are placing their arm properly during the BP measurement. The application can indicate to the user whether they should move their arm up or down to bring it to the proper position. It must be clarified that the current system is limited to detecting this particular movement of the arm up and down across the chest; we assume that the arm is still close to the chest and the elbow remains in the same position.

We also further looked into our device to see how accurately it can classify the arm position using y-axis accelerometer data. In a separate more comprehensive test, readings for g_y were taken in several different arm positions and a *k*-nearest neighbor (*k*-NN) classifier was used to classify each g_y value to one of about 16 different arm positions. To be sure, k-NN classifier is used merely to validate our accelerometer's accuracy in the absence of a golden standard. The classifier is not used as part of the angle or gravity measurements and is not part of the usual signal processing flow of BioWatch. The experimental protocol is explained in detail in Section V-C while the accuracy of the classifier is reported in Section VI-E.

V. Experimental Setup

The experiments for gathering PTT and BP data were conducted at the University of North Texas Health Science Center. A total of 11 healthy subjects participated in the experiment and written consent was obtained from all of them. The protocol and consent were approved by the IRB at the UNT Health Science Center. The tests for position detection were conducted at The University of Texas at Dallas with a total of 4 subjects participating in it. The protocol and consent were approved by the IRB at The University of Texas at Dallas.

A. Measurement Procedure for PTT-BP study

For measuring the PTT and the reference BP we needed to use both hands of the subject. BioWatch was worn on the left wrist to collect both ECG and PPG. With the help of a trained technician we used the Colin Continuous Blood Pressure Monitor, CBM-7000 as the reference device for ABP. It collects beat-to-beat ABP from the radial artery using the right arm and the right wrist. This device is itself calibrated to a standard BP cuff at the beginning of each measurement cycle and then continues to collect indirect ABP from the wrist using its wrist-worn module. The ABP recorded is sent to the PC through BIOPAC MP150, which also records another ECG signal from the subject simultaneously. This ECG is taken across the heart and is also used to align the data from both BioWatch and reference device. To control the height of the sensor and keep it consistent, we decided to keep all the measurements at chest level. Since in this experiment the right arm was used to collect the ABP, we used a wire connecting from the top ECG electrode to the right hand to complete the electrical connection for ECG on the BioWatch.

B. Protocol for PTT-BP study

Once the subject is ready for data collection he/she is asked to assume the standing position for the first set of data collection. Our aim was to make sure that the BP is accurately measured during normal conditions as well as during periods of fluctuation of BP. Keeping this in mind, we added the Valsalva maneuver to the experimental protocol [30]. This helps in bringing sharp changes in BP for a brief amount of time. The Valsalva maneuver required the subject to exhale against the closed airway after the maximal inhalation (at the maximal lung volume) to induce the required change. The subject is at rest during the first 4 minutes of the data collection. This gives us enough time to get the PTT and BP measurements dusing normal conditions. After that, the Valsalva maneuver was performed 5 times. A 45 seconds to 1 min gap is maintained between each one. The total time taken for data collection for one posture for each subject is around 10 to 12 minutes. This same procedure is repeated in sitting position and supine position. The collected data was imported to MATLAB for further processing. The reference SBP and DBP are also obtained from the ABP device. With the help of the two ECG signals from both BioWatch and the reference device, the data can be aligned. The data is visually checked and any data segments with motion artifacts are removed for accurate PTT calculation. Using the calculated PTT and the reference SBP and PP, we trained a PTT-SBP and PTT-PP equations. For validation we found the RMSE between the calculated BP and the real measured BP on an untrained data segment. Fig. 7 shows the PTT and SBP measured simultaneously during the Valsalva maneuver and the results are reported in Section VI.

C. Protocol used for development of arm position classifier

For this test we used 3 test subjects. We noted their arm length, initial arm position, position A in Fig. 6, which is used for training and the corresponding y-axis measurement g_y. Using these measurements the allowable g_y range is calculated using the methods described in Section IV-C. The subject is asked to keep his/her arm in different positions 2cm apart. Measurements in each position were repeated five times and the corresponding g_y values were noted. A total of 15 to 17 positions are used for test, as indicated by the circles in Fig. 6 where every two circles are 2cm apart. Using *k*-NN algorithm and leave-one-out cross validation (LOOCV) we further use this data to see how well the device can classify among these positions. We used 4 out of the 5 values in each position as the training set and the left out value from each position is tested and classified using the *k*-NN algorithm and this is repeated for each of the 5 values as per LOOCV.

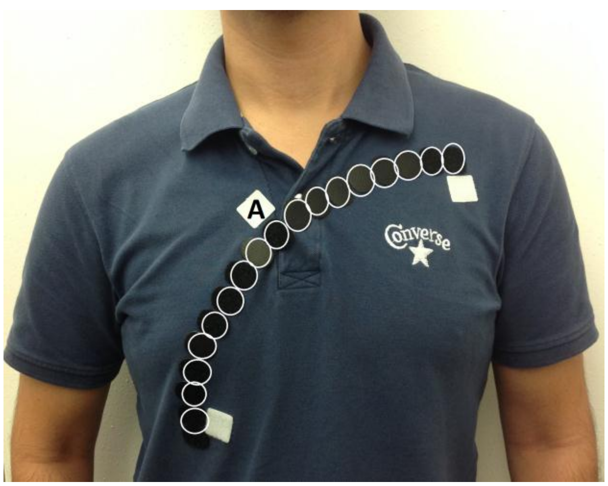

Fig. 6: Different positions used for arm position detection test

VI. Discussion and Results

A. Correlation between PTT and BP

As expected we observed a negative correlation between PTT and SBP. The highest negative Pearson correlation coefficient we observed was 0.88 and the lowest negative correlation coefficient was 0.25. Taking average across the 11 subjects the observed negative correlation coefficients were 0.64, 0.55 and 0.74 for supine, sitting and standing postures respectively. The fact that the correlations were different for each subject and posture shows that any calibration or algorithm developed to calculate BP from PTT needs to take into consideration both the posture and the individual. Fig. 7 shows how PTT varies as SBP varies for one of the individuals during the Valsalva maneuver. We also found that the average correlation coefficient between PTT and reference DBP was as low as 0.38±0.21 confirming the findings from previous studies. The correlation coefficient between PTT and PP on the other hand was 0.65±0.17, thus making it a good proxy to train and use to estimate DBP.

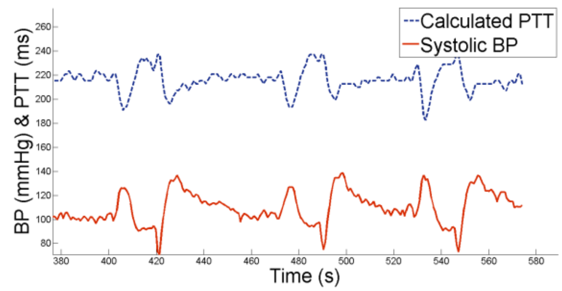

Fig. 7: PTT & BP collected simultaneously

B. Change in PTT and SBP during posture changes

Table II shows the mean systolic BP from the reference device and mean PTT collected during each posture for each individual. Each value is the average of the continuous SBP and PTT collected during the entire time segment for each posture. Table II shows how both SBP and PTT changes differently across different individuals. For example, in the sitting posture, Subject 1 and Subject 3 have the same SBP but their PTTs differ by 35ms. Moreover, when the posture changes from sitting to standing, SBP increases in the case of Subject 1 but decreases in the case of Subject 3. The PTT however decreases for both subjects. Finally, Fig. 8 shows the scatter plot of BP and PTT for a single individual for 3 different postures and we can see there are significant differences. These observations indicate that a PTT-SBP equation trained for one posture/subject will not hold true for another. This notion will be further analyzed and quantified in Section VI-D.

Table II: Average Systolic BP collected from individuals and their corresponding measured Average Pulse Transit Time.

Subject No	Systolic BP (mmHg) and Pulse Transit Time (ms)					
	Supine		*Sitting*		*Standing*	
	SBP	*PTT*	*SBP*	*PTT*	*SBP*	*PTT*
1	105	256	118	293	133	271
2	96	270	107	262	112	256
3	105	221	118	224	81	222
4	93	292	104	291	103	300
5	129	264	113	253	110	276
6	111	267	95	277	107	259
7	108	277	97	289	110	281
8	112	236	113	245	128	245
9	150	248	113	270	104	279
10	102	272	110	249	98	255
11	124	279	118	277	115	274

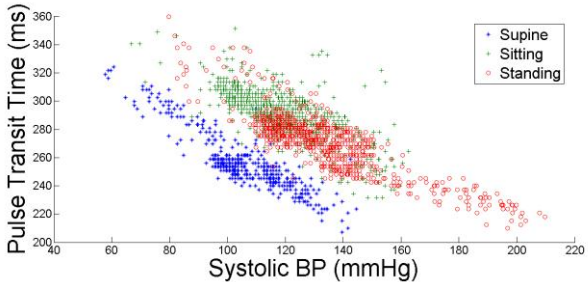

Fig. 8: Scatter plot of PTT & BP collected from the same subject during Supine, Sitting and Standing postures.

C. Root Mean Square Error

For each subject, we trained the PTT-SBP equation on data from each posture and calculated the SBP using this equation. Similarly, we trained PTT-PP equations and computed DBP using the calculated SBP and PP. The RMSE between the calculated BP from BioWatch and the actual measured BP from the reference device was computed on the untrained segments for each of the postures. These results are then averaged across all subjects for each of the fitting functions as shown in Tables III and IV for SBP and DBP respectively. We observed low average RMSEs across all postures ranging between 7.83mmHg to 9.37mmHg for SBP and between 5.77mmHg and 6.90mmHg for DBP. The maximal RMSE over all subjects and postures is 14.27mmHg and 9.68mmHg for SBP and DBP, respectively. The 95% confidence intervals for the RMSE for both SBP and DBP are shown in Tables V and VI. These results validate the feasibility of PTT-based BP measurement on a wrist-based device. Fig. 9 shows the fitted systolic BP and the measured systolic BP during the Valsalva maneuver for one of the subjects. Similarly, Fig. 10 shows the fitted and measured DBP during the Valsalva maneuver for a subject.

In general, the DBP estimates were better, both in terms of average RMSE as well as the tightness of the confidence interval. Moreover, the 'standing' position resulted in relatively poorer performance compared to the other postures.

Table III: RMSE between calculated SBP and measured SBP

Fitting Function:	RMSE for Different Postures in mmHg (mean$\pm$*std*)		
	Supine	*Sitting*	*Standing*
1	7.90$\pm$1.60	8.88$\pm$2.30	9.36$\pm$2.06
2	7.86$\pm$1.64	8.86$\pm$2.39	9.14$\pm$2.19
3	7.92$\pm$1.64	8.90$\pm$2.30	9.35$\pm$2.03
4	7.83$\pm$1.64	8.80$\pm$2.42	9.06$\pm$2.21
5	7.95$\pm$1.65	8.90$\pm$2.30	9.37$\pm$2.07

Table IV: RMSE between calculated DBP and measured DBP

Fitting Function:	RMSE for Different Postures in mmHg (mean$\pm$*std*)		
	Supine	*Sitting*	*Standing*
1	5.88$\pm$1.62	5.97$\pm$1.15	6.90$\pm$2.02
2	5.77$\pm$1.71	5.97$\pm$1.28	6.68$\pm$1.95
3	5.86$\pm$1.64	5.96$\pm$1.17	6.87$\pm$1.99
4	5.78$\pm$1.66	6.09$\pm$1.22	6.72$\pm$1.95
5	5.86$\pm$1.63	5.97$\pm$1.18	6.89$\pm$2.02

Table V: 95% confidence intervals for RMSE of SBP estimates

Fitting Function:	95% confidence intervals for different postures in mmHg		
	Supine	*Sitting*	*Standing*
1	[-16.837,16.971]	[-19.240,19.410]	[-20.045,20.214]
2	[-16.760,16.749]	[-19.284,19.416]	[-19.691,19.836]
3	[-16.908,16.933]	[-19.292,19.454]	[-19.995,20.154]
4	[-17.232,17.496]	[-20.555,21.208]	[-20.546,21.020]
5	[-18.137,17.815]	[-19.749,19.675]	[-22.917,22.410]

Table VI: 95% confidence intervals for RMSE of DBP estimates

Fitting Function:	95% confidence intervals for different postures in mmHg		
	Supine	*Sitting*	*Standing*
1	[-13.120,13.133]	[-13.003,13.142]	[-15.340,15.408]
2	[-12.938,12.936]	[-13.112,13.169]	[-15.148,15.199]
3	[-13.102,13.112]	[-12.997,13.133]	[-15.303,15.371]
4	[-13.626,13.939]	[-14.705,15.355]	[-17.248,18.330]
5	[-13.312,13.234]	[-13.376,13.517]	[-15.415,15.551]

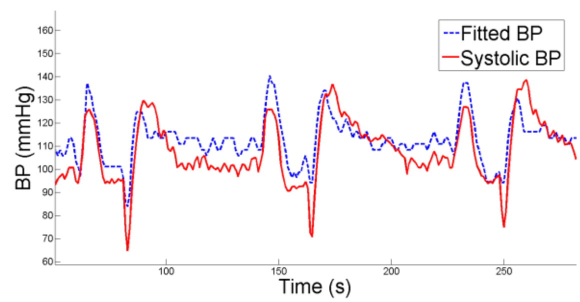

Fig. 9: Fitted BP & corresponding systolic BP

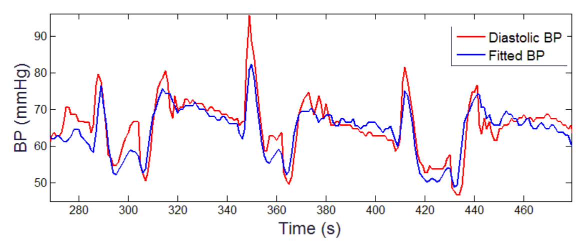

Fig. 10: Fitted BP & corresponding diastolic BP

If we consider the results across different fitting equations we do not find any large variations in performance between the equations. This means that in eventual deployment and online processing on a microcontroller, a simple equation might suffice. Fig. 11 shows the plot of PWV against the actual systolic BP and the fitted BP from the 5 fitting equations on one subject. The results are largely similar for DBP as well.

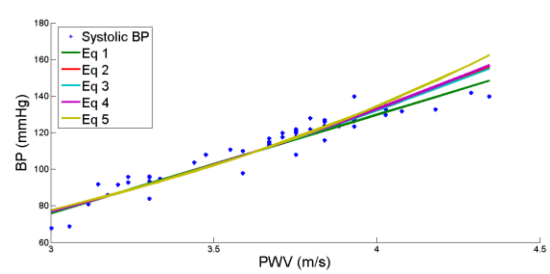

Fig. 11: PWV Vs actual systolic BP & Fitted BP

In [31], authors conclude that calibration that accounts for a variety of possible BP points is important for the overall accuracy of the device. Accordingly, the PTT equations developed in this work is calibrated across a wide range of BP variations. The average SBP change during the Valsalva maneuver across all subjects is 90mmHg. Consequently, the methods described here can be expected to provide more accurate results under varying conditions.

D. Individual Specific and Posture Specific Training

Apart from the method, shown in Section VI-C, for generating Tables III and IV, we also generated Tables VII & VIII to test the importance of training the equation to specific postures and individuals. The equations were first trained using data from all the postures of the same subject. This equation is tested on the untrained segment of the data on each posture of the same induvidual. The RMSEs calculated using this method and their percentage increase from the Table III SBP results are shown in Table VII. The increase in RMSE shows that a posture specific training always yields better results than training without regard to posture.

We also wanted to evaluate the results when training the equation on the same posture across all subjects. This equation is then tested on the untrained data from the same posture of each individual. The results in Table VIII again show a significant increase in the RMSE. This led to the conclusion that not only posture-specific, but also individual-specific training significantly improves the performance of the system.

Table VII: RMSE from equation trained on all postures and percentage increase on RMSE when compared to posture specific trained BP

Fitting Function	Percentage increase on RMSE in mmHg					
	Supine		*Sitting*		*Standing*	
	RMSE	*% increase*	*RMSE*	*% increase*	*RMSE*	*% increase*
1	12.30	55.51%	10.68	20.17%	12.13	29.58%
2	12.11	54.03%	10.78	21.57%	12.01	31.37%
3	12.33	55.63%	10.68	20.06%	12.09	29.38%
4	12.10	54.57%	10.78	22.48%	12.02	32.58%
5	12.38	55.76%	10.65	19.63%	12.07	28.75%

Table VIII: RMSE from equation trained on all subjects and percentage increase on RMSE when compared to subject specific trained BP

Fitting Function	Percentage increase on RMSE in mmHg					
	Supine		*Sitting*		*Standing*	
	RMSE	*% increase*	*RMSE*	*% increase*	*RMSE*	*% increase*
1	14.58	84.44%	11.14	25.37%	16.81	79.56%
2	14.56	85.18%	11.15	25.77%	16.69	82.60%
3	14.64	84.71%	11.14	25.14%	16.86	80.37%
4	14.51	85.22%	11.15	26.64%	16.62	83.35%
5	14.65	84.35%	11.13	25.04%	16.84	79.61%

E. Position Detection Accuracy

Table IX shows the value of PTT, SBP and g_y measured on one individual for the different arm positions defined in Figure 4. This test was done to confirm the effects of arm position changes on the PTT. Here the SBP is calculated from the measured PTT. The table shows that the PTT and BP changes significantly with different arm positions. About 15% change in SBP can be noted from position E to position A. A simple position detection of the arm can ensure that the accuracy is maximized.

Table IX: g_y, PTT & BP values at different arm positions

Arm Positions:	g_y, PTT and SBP values for different arm positions		
	y-axis (g_y)	*PTT (mS)*	*SBP (mmHg)*
A	0	266	115
B	0.25	273	110
C	0.58	279	105
D	0.7	282	103
E	0.955	286	100

The g_y value shown in position C in Fig. 4 is considered to be the proper position of the arm. This value will differ slightly between individuals since the arm length and other body characteristics of each individual can be different. During the training phase for each individual this g_y value is recorded and the acceptable range of g_y is calculated (as explained in Section IV-C) to indicate proper arm position for any future readings. The GUI displaying the measured BP can then indicate whether the user has placed the arm in the proper position that was used for training by simply monitoring the g_y value of the accelerometer and ensuring it is in the correct range.

To test the effectiveness of this arm position detection based on g_y measurements, we tested the accuracy of the k-NN classifier defined previously in Section V-C. The value of k is set to be the total number of positions tested for each subject, which varied from 15 to 17. Any time there is a tie between two or more sets of neighbors belonging to different classes, we choose the class with the set of neighbors that has the lowest cumulative distance to the tested input. When evaluating the ability to classify within ±2cm of the actual position, the accuracy of the classifier was 98%.

The arm position detection described in Section IV-C can be used for both sitting and standing postures. Currently this technique cannot be used for the supine posture since the effect of gravity on all three axes during arm movement remains the same and more sophisticated signal processing would be required. For arm position detection, the current implementation is just an initial foray to deal with certain arm position changes. Further improvement is also desirable by developing algorithms such that the PTT/PWV- BP equation adjusts itself with the change in the arm position. Such extensive techniques was not in the current scope of the manuscript but will be investigated in the future.

VII. Conclusion

In this paper, we presented a wrist-based platform for continuous BP monitoring. The device measures PTT which is then converted to BP using appropriate fitting functions. We observed that PTT and BP values change significantly across different postures and different individuals. We proposed a unified method to train, develop and calibrate PTT-BP equation to each individual and posture. We are yet to evaluate the long term effectiveness of this approach and the necessity and frequency of future training or calibrations due to advancement in age and ailments. However in the short term this method gives us a way to measure individual and posture calibrated BP without the need for considering many other characteristics such as PEP, age etc. RMSEs in the range of 5.77 to 6.90mmHg for DBP and 7.8mmHg to 9.37mmHg for SBP are obtained using the described techniques. This method also relies on correct arm position when measuring BP and we have provided a built-in solution based on an accelerometer to automatically detect the arm position with an accuracy of 98%. The proposed noninvasive wireless solution of BioWatch could potentially provide a convenient, wearable solution for continuous BP monitoring.

Acknowledgment

We thank Ebunoluwa Akinbola for her assistance during data collection.

References

[1] S. L. Murphy, J. Xu, and K. D. Kochanek, "Deaths: final data for 2010," *National vital statistics reports*, vol. 61, no. 4, pp. 1–118, 2013.

[2] C. Poon and Y. Zhang, "Cuff-less and noninvasive measurements of arterial blood pressure by pulse transit time," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pp. 5877–5880, IEEE, 2006.

[3] E. J. Ciaccio and G. M. Drzewiecki, "Tonometric arterial pulse sensor with noise cancellation," *Biomedical Engineering, IEEE Transactions on*, vol. 55, no. 10, pp. 2388–2396, 2008.

[4] M. Park, H. J. Kang, Y. Huh, and K.-C. Kim, "Cuffless and noninvasive measurement of systolic blood pressure, diastolic blood pressure, mean arterial pressure and pulse pressure using radial artery tonometry pressure sensor with concept of korean traditional medicine," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pp. 3597–3600, IEEE, 2007.

[5] A. Hennig and A. Patzak, "Continuous blood pressure measurement using pulse transit time," *Somnologie-Schlafforschung und Schlafmedizin*, vol. 17, no. 2, pp. 104–110, 2013.

[6] F. S. Cattivelli and H. Garudadri, "Noninvasive cuffless estimation of blood pressure from pulse arrival time and heart rate with adaptive calibration," in *Wearable and Implantable Body Sensor Networks, 2009. BSN 2009. Sixth International Workshop on*, pp. 114–119, IEEE, 2009.

[7] C. Ahlstrom, A. Johansson, F. Uhlin, T. Länne, and P. Ask, "Noninvasive investigation of blood pressure changes using the pulse wave transit time: a novel approach in the monitoring of hemodialysis patients," *Journal of Artificial Organs*, vol. 8, no. 3, pp. 192–197, 2005.

[8] V. Chandrasekaran, R. Dantu, S. Jonnada, S. Thiyagaraja, and K. Subbu, "Cuffless differential blood pressure estimation using smart phones," *Biomedical Engineering, IEEE Transactions on*, vol. 60, pp. 1080–1089, April 2013.

[9] P. Fung, G. Dumont, C. Ries, C. Mott, and M. Ansermino, "Continuous noninvasive blood pressure measurement by pulse transit time," in *Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE*, vol. 1, pp. 738–741, IEEE, 2004.

[10] Y. Li, Z. Wang, L. Zhang, X. Yang, and J. Song, "Characters available in photoplethysmogram for blood pressure estimation: beyond the pulse transit time," *Australasian Physical & Engineering Sciences in Medicine*, vol. 37, no. 2, pp. 367–376, 2014.

[11] J. Lass, K. Meigas, D. Karai, R. Kattai, J. Kaik, and M. Rossmann, "Continuous blood pressure monitoring during exercise using pulse wave transit time measurement," in *Engineering in Medicine and Biology Society, 2004. IEMBS'04. 26th Annual International Conference of the IEEE*, vol. 1, pp. 2239–2242, IEEE, 2004.

[12] T. Ma and Y. Zhang, "A correlation study on the variabilities in pulse transit time, blood pressure, and heart rate recorded simultaneously from healthy subjects," in *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*, pp. 996–999, IEEE, 2005.

[13] Y. Zheng, B. P. Yan, Y. Zhang, C. Yu, and C. C. Poon, "Wearable cuff-less ptt-based system for overnight blood pressure monitoring," in *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*, pp. 6103–6106, IEEE, 2013.

[14] Y. Kim and J. Lee, "Cuffless and non-invasive estimation of a continuous blood pressure based on ptt," in *Information Technology Convergence and Services (ITCS), 2010 2nd International Conference on*, pp. 1–4, IEEE, 2010.

[15] J. J. Furedy, A. Szabo, and F. Péronnet, "Effects of psychological and physiological challenges on heart rate, t-wave amplitude, and pulse-transit time," *International journal of psychophysiology*, vol. 22, no. 3, pp. 173–183, 1996.

[16] M. Gellman, S. Spitzer, G. Ironson, M. Llabre, P. Saab, R. D. Pasin, D. J. Weidler, and N. Schneiderman, "Posture, place, and mood effects on ambulatory blood pressure," *Psychophysiology*, vol. 27, no. 5, pp. 544–551, 1990.

[17] F. Caird, G. Andrews, and R. Kennedy, "Effect of posture on blood pressure in the elderly.," *British heart journal*, vol. 35, no. 5, p. 527, 1973.

[18] C. J. Nardo, L. E. Chambless, K. C. Light, W. D. Rosamond, A. R. Sharrett, G. S. Tell, and G. Heiss, "Descriptive epidemiology of blood pressure response to change in body position the aric study," *Hypertension*, vol. 33, no. 5, pp. 1123–1129, 1999.

[19] J. Muehlsteff, X. Aubert, and G. Morren, "Continuous cuff-less blood pressure monitoring based on the pulse arrival time approach: The impact of posture," in *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE*, pp. 1691–1694, IEEE, 2008.

[20] H. Gesche, D. Grosskurth, G. Küchler, and A. Patzak, "Continuous blood pressure measurement by using the pulse transit time: comparison to a cuff-based method," *European journal of applied physiology*, vol. 112, no. 1, pp. 309–315, 2012.

[21] A. Jadooei, O. Zaderykhin, and V. Shulgin, "Adaptive algorithm for continuous monitoring of blood pressure using a pulse transit time," in *Electronics and Nanotechnology (ELNANO), 2013 IEEE XXXIII International Scientific Conference*, pp. 297–301, IEEE, 2013.

[22] Q. Zhang, Y. Shi, D. Teng, A. Dinh, S.-B. Ko, L. Chen, J. Basran, D. Bello-Haas, Y. Choi, *et al.*, "Pulse transit time-based blood pressure estimation using hilbert-huang transform," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, pp. 1785–1788, IEEE, 2009.

[23] Y. Yoon, J. H. Cho, and G. Yoon, "Non-constrained blood pressure monitoring using ecg and ppg for personal healthcare," *Journal of medical systems*, vol. 33, no. 4, pp. 261–266, 2009.

[24] G. S. Chan, P. M. Middleton, B. G. Celler, L. Wang, and N. H. Lovell, "Change in pulse transit time and pre-ejection period during head-up tilt-induced progressive central hypovolaemia," *Journal of clinical monitoring and computing*, vol. 21, no. 5, pp. 283–293, 2007.

[25] J. H. Houtveen, P. F. Groot, and E. J. Geus, "Effects of variation in posture and respiration on rsa and pre-ejection period," *Psychophysiology*, vol. 42, no. 6, pp. 713–719, 2005.

[26] S. S. Thomas, V. Nathan, C. Zong, P. Aroul, L. Philipose, K. Soundarapandian, X. Shi, and R. Jafari, "Demonstration abstract: Biowatch: a wrist watch based physiological signal acquisition system," in *Proceedings of the 13th international symposium on Information processing in sensor networks*, pp. 349–350, IEEE Press, 2014.

[27] S. S. Thomas, V. Nathan, C. Zong, E. Akinbola, A. L. P. Aroul, L. Philipose, K. Soundarapandian, X. Shi, and R. Jafari, "Biowatch—a wrist watch based signal acquisition system for physiological signals including blood pressure," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, pp. 2286–2289, IEEE, 2014.

[28] H. A. Nygaard, "Measuring body mass index (bmi) in nursing home residents: the usefulness of measurement of arm span," *Scandinavian journal of primary health care*, vol. 26, no. 1, pp. 46–49, 2008.

[29] C. C. Poon and Y.-T. Zhang, "Using the changes in hydrostatic pressure and pulse transit time to measure arterial blood pressure," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, pp. 2336–2337, IEEE, 2007.

[30] R. Gorlin, J. H. Knowles, and C. F. Storey, "The valsalva maneuver as a test of cardiac function: pathologic physiology and clinical significance," *The American journal of medicine*, vol. 22, no. 2, pp. 197–212, 1957.

[31] I. R. Yan, C. C. Poon, and Y. Zhang, "A protocol design for evaluation of wearable cuff-less blood pressure measuring devices," in *Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE*, pp. 7045–7047, IEEE, 2009.

Simi Susan Thomas received her BSc degree in electronics from University of Calicut, Kerala, India in 2001 and her MSc degree in electronics from Bharathiar University in 2004. She is currently pursuing her M.S thesis in computer engineering from The University of Texas at Dallas, Richardson, Texas, USA.

She is currently working as Teaching Assistant at The University of Texas at Dallas. She was also working as a Research Assistant for a year for the same university. She has about two and half years of previous experience developing different embedded systems. Her research interests include development of embedded systems for different applications including wearable sensors and medical electronics.

Viswam Nathan received his B.S. and M.S. degrees in computer engineering from the University of Texas at Dallas in 2012 and 2015 respectively.

He is currently working toward his Ph.D. degree in computer engineering at Texas A&M University. His research interests include design and development of a wearable and reconfigurable health monitoring devices as well as signal processing techniques to assess the quality and reliability of the acquired signal.

Chengzhi Zong received the B.S. degree in Information Engineering from Southeast University, Nanjing, China and the M.S. degree in Electrical Engineering from New York University Polytechnic School of Engineering, Brooklyn, NY in 2010 and 2012 respectively. He is currently working toward Ph.D. degree in Electrical Engineering at University of Texas at Dallas. His research includes the design and implementation of digital signal processing and machine learning algorithms for the cyber physical systems for various medical applications.

Karthikeyan Soundarapandian is the Segment Manager for Health and Fitness at Texas Instruments. He received his Masters in Compter engineering from Iowa State University in 1998. Since then he has been working at Texas Instruments driving innovations in next generation healthcare technologies. His area of expertise includes low power mixed signal analog design with specific focus on high precision Delta-Sigma Analog to Digital converters. He is a Member Group Technical Staff at Texas Instruments and a senior member of IEEE since 2005. He has published over 10 papers in refereed journals and conferences and holds 5 US patents in the area of mixed signal analog design.

Xiangrong Shi obtained his Ph.D. from Yale University. His research interests focus on applying alternative interventions for prevention and treatment of obesity, aging, cardiovascular and neurologic conditions; and novel bio-engineering apparatus in non-invasive monitoring and regulation of cardiovascular function. Currently, Dr. Shi is an associate professor at the University of North Texas Health Science Center.

Roozbeh Jafari (SM'12) is an associate professor in Biomedical Engineering, Computer Science and Engineering and Electrical and Computer Engineering at Texas A&M University. He received his PhD in Computer Science from UCLA and completed a postdoctoral fellowship at UC-Berkeley. His research interest lies in the area of wearable computer design and signal processing. His research has been funded by the NSF, NIH, DoD (TATRC), AFRL, AFOSR, DARPA, SRC and industry (Texas Instruments, Tektronix, Samsung & Telecom Italia). He has published over 100 papers in refereed journals and conferences. He has served as the general chair and technical program committee chair for several flagship conferences in the area of Wearable Computers including the ACM Wireless Health 2012 and 2013, International Conference on Body Sensor Networks 2011 and International Conference on Body Area Networks 2011. He is the recipient of the NSF CAREER award in 2012, IEEE Real-Time & Embedded Technology & Applications Symposium (RTAS) best paper award in 2011 and Andrew P. Sage best transactions paper award from IEEE Systems, Man and Cybernetics Society in 2014. He is an associate editor for the IEEE Sensors Journal, IEEE Internet of Things Journal and IEEE Journal of Biomedical and Health Informatics.