Non-invasive Blood Pressure estimation using constitutive model from the radial artery pulse

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***Abstract*—Blood Pressure (BP) is a vital parameter for monitoring the wellness of an individual; as any extremity in its value (low or high) could be fatal, making the continuous monitoring of BP extremely important. This paper aims to develop an algorithm that estimates BP non-invasively using arterial displacement pulse. The constitutive model governs the relationship between change in radial arterial waveform w.r.t radius change and the pressure. Further, to improve the accuracy of estimated BP, a probabilistic inference method by Markov sampling was performed. Proposed approach estimated both systolic and diastolic blood pressure with an RMSE value of 11 and 6 mmHg for systolic (P_s) and diastolic (P_d) pressures respectively. In addition to BP estimation, proposed model was able to estimate the mean radius of the artery with 95% accuracy.**

I. INTRODUCTION

It is believed that mean arterial pressure more than 60 mmHg is important for the adequate cellular perfusion of oxygen. A very low blood pressure (BP) could be associated with shock though it doesn't necessarily indicate it. It has been reported that shock is a very dangerous situation where the tissues are deprived of oxygen resulting in dizziness and neurological damage [1]. A high blood pressure on the other hand is a risk factor for different diseases such as stroke, chronic kidney disease, and aneurysms. Even though the a range of BP which could be classified as high and low is well understood, it may vary for each and every individual [2]. This makes the measurement of blood pressure a very important and a vital parameter to be continuously monitor.

Currently there exist several algorithms which use PPG (Photo plethysmography) and ECG (Electrocardiogram) signals for blood pressure monitoring [3-5]. Long-term application of light and pressure are known to cause skin integrity issues in patients such as burns due to equipment related issues [6-8]. There are also conditions such as low blood flow which in turn causing minimal heat dissipation causing injuries to the patient [9]. This pave way for an alternative or improvised methods for BP estimation. In this study we have proposed a novel approach that measures the radial artery pulse and estimates BP using a constitutive model of the artery.

II. METHODOLOGY

A. PIEZOELECTRIC SENSOR INPUT

Piezoelectric sensor has been used to detect the displacement waveforms from the radial artery pulse. Sensors are placed to the locations proximal to the styloid process on the dorsal side of the wrist exposes the radial artery to a great extent [10]. These sensors are transducers which convert the displacements on the arterial surface into an electric voltage. This is further converted back into displacement information using an appropriate conversion factor. Parameters (E, h) appropriate to these regions were adapted from literature [10-12] for the simulation. Actual blood pressure data was collected after collecting the displacement waveforms using a calibrated sphygmomanometer.

B. MATHEMATICAL MODEL

Further, mathematical model chosen is Voight type viscoelastic cylinder as an abstraction to simulate these tissue layers [11-12]. A Voight type viscoelastic material consists of a Hookian and viscous resistive elements [11-12]. The following set of equations relates the blood pressure to the change in the area of the artery. All the variables and parameters are described in Table 1

$$P = P_{ext} + \frac{\beta}{A_0}(\sqrt{A} - \sqrt{A_0}) + \Gamma\frac{\partial A}{\partial t} \qquad (1)$$

$$\beta = (\frac{4}{3})\sqrt{\pi}E(P)h\frac{1}{A_0} \qquad (2)$$

$$\Gamma = \frac{\gamma}{2\sqrt{\pi A_0}} \qquad (3)$$

$$A = \pi r^2 \qquad (4)$$

Where

Table I: The parameters and variables of the model and its descriptions

Variables/Parameters	Explanations
P	Pressure inside the artery

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P_{ext}	Pressure applied externally
A	Cross sectional area of the artery – Artery is assumed circular
A_0	Cross sectional area of the artery at zero transmural pressure
μ	Fluid viscocity
E	Modulus of elasticity of the arterial wall although a function of strain and thus P here it is assumed constant
h	Wall thickness of the artery
β	Stiffness parameter
Γ	Damping coefficient
r	Radius of the artery

The external pressure (P_{ext}) is assumed to be zero as the sensor measures the radial artery pressures without any external pressure application. As mentioned before in section B the viscoelastic tissue has elastic as well as fluid mechanical properties that resist the force applied by changing its length by hook's law.

The stiffness parameter β is proportional to this resistance offered by the elastic walls of the artery [12] [9]. The fluid mechanical properties take effect when the system resists a rate of change in displacement. The rate of change of the displacement faces a resistance similar to that of a body moving in a viscous fluid. It is evident from the equations that the parameter Γ converts the rate of displacements to the pressure taking care of the fluid-mechanical properties of the viscoelastic tissue.

C. Arterial mean radius model

The measured displacement signals from the piezo sensor are assumed to be directly correlated with the changes in radius of the vessel wall. Thus the relationship between the change in the radius of the artery and measured displacement $d(t)$ is assumed to be governed by equation 5.

$$r(t) = r_{mean} + (d(t) - \frac{\sum d(t)}{n}) \tag{5}$$

Where

r_{mean} is the mean radius of the radial artery

$r(t)$ is the instantaneous radius of the artery

$d(t)$ the time varying displacement measured

And n the number of elements in the time window of measurement.

r_{mean} is estimated using an ANN-Levenberg–Marquardt(LM) algorithm [4] as shown in figure 1.

The stress strain relationships and the response to pressure input of the vessel wall are highly dependent on the instantaneous radius of the arteries and thus the mean radius of the artery. In other words the creep and relaxation behavior of the artery is different for different mean radii that is based on the response to pressure loading. That makes the mean radius information to be embedded in the response of the vessel to pressure loading from the heart. This idea is the rationale for using neural network algorithm in estimating the mean radius of the artery from the frequency content of the $d(t)$waveform.

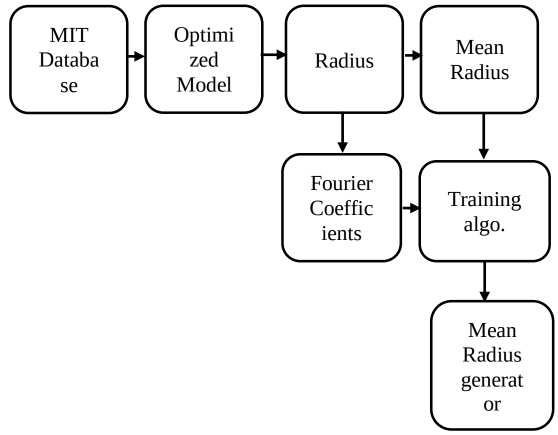

Figure 1: Functional flowchart representation of the Arterial mean radius model. The data from MIT Physionet is fed to the model and its solution "radius" is processed to extract mean radius and Fourier coefficients. This in turn is feed to the neural network algorithm to generate a "map" that takes Fourier coefficients to the mean arterial radius.

The radius obtained from the optimized model is partitioned into a set of 128 $\times$384 data and mean radius is extracted from the data (Figure 1). Fourier coefficients are also extracted as shown in the Figure 1 from the same radius data window. The Fourier coefficients and the extracted mean radii are then used in the training algorithm to generate a function which estimates the mean radius.

D. Optimization of the parameter γ using genetic algorithm

The equation (5) along with the constitutive model [11-13] is used in estimating the pressure inside the vessel. The systolic (P_s) and diastolic(P_d) pressures are then estimated by finding the mean of the peaks of the blood pressure waveform and minimum of the waveform respectively.

The l_1 distance between the estimated BP (using equations 1-5) and the measured BP for a dataset is then used as a cost function for optimization. This problem of optimization is nonlinear as the differential equation contains square root terms of the state variable. We used genetic algorithm to minimize the cost function for an optimal set of parameters.

$$Cost = |BP_{estimated} - BP_{measured}| \tag{6}$$

Problem solved using the genetic algorithm: Find parameters γ such that "cost" is minimized. The GA optimization(Figure 2) was started with population size of 50. The algorithm is run till convergence.

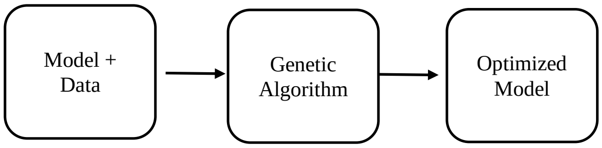

Figure 2: Genetic algorithm with $l_1$distance cost function is used in optimizing the model. The GA makes use of population type bit string, crossover ratio of 0.8, constraint tolerance of 10^{-6}, and function tolerance of 10^{-4}. Elitist method (*MATLAB 2014 optimization toolbox*) was used for selection.

E. The algorithm for BP estimation

The "map" which generates the mean radius from the Fourier coefficients and the optimized model is used to estimate the blood pressure. This map is then used to estimate the mean radius in the algorithm.

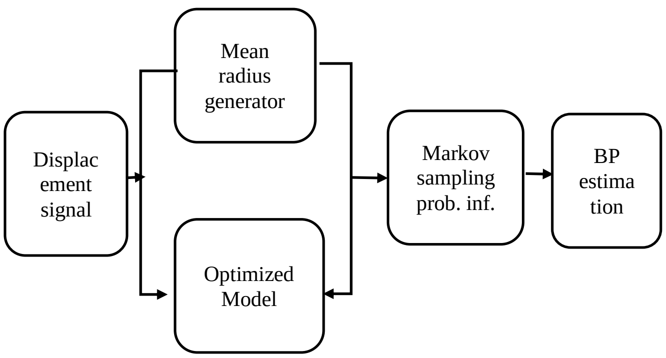

Figure 3: The complete algorithm for BP estimation. The displacement signal is feed into the optimized model and mean radius generator which gives out a set of probable values for the blood pressure for the sampled set of parameters (E and h). This estimate is then feed into the probabilistic inference set up to determine the maximum likely BP.

A set of blood pressure estimates is generated using a set of probable parameters (E and h) taken from an appropriate distribution. This distribution could be tuned to match the subjects' physiological conditions for personalization. The most likely value of the blood pressure is then estimated from these sets using maximum likelihood estimation. This probabilistic sampling framework helps to further personalize the estimation algorithm and use it for better inference (Figure 3).

III. RESULTS AND DISCUSSION

The data from MIT Physio-net is used to estimate the mean arterial radius. We have extracted 40 Fourier coefficients (20 real and 20 imaginary) and their corresponding mean radius to train the ANN – LM algorithm. The ANN consists of 12 hidden layers which takes the Fourier coefficients of the r(t) to the mean radius. The number of samples used were 384 of which 70% (268) was used for training 15 % (57) for testing and 15%(57) for validation. The neural network algorithm fits the data with an accuracy of 92% in testing and 95% in validation. The efficiency to estimate the arterial radius is shown in figure 4.

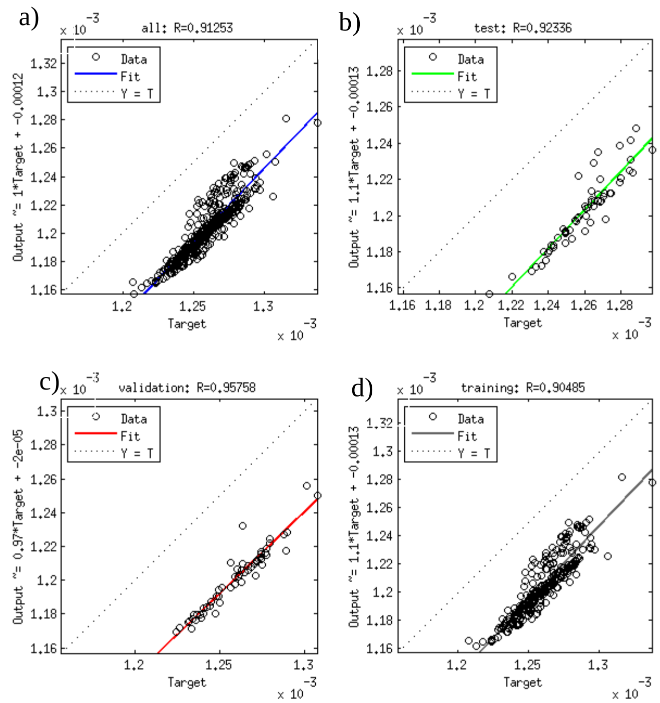

Figure 4: Performance of the neural network algorithm for the training, validation, test and all data sets. The neural network algorithm fits the data with an accuracy of 92% in testing and 95% in validation. a) Regression result of all data together this includes training test and validation b) regression result of test data c) regression result of validation data this is used for regularization of the neural networks to keep its generality intact d) The regression analysis of training data. A function relating the output and target is shown for clarity.

Using the optimized the parameters, BP was estimated and validated for 11 test sets. The Error (equations 8, 9) was plotted for P_s (Figure 5) and P_d (Figure 6).

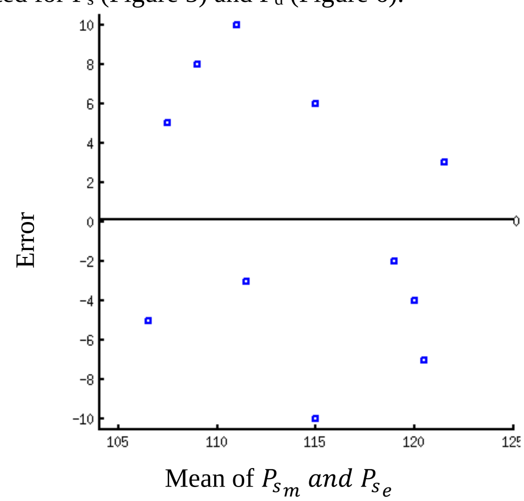

Figure 5: The plot shows how Error (Equation 7) varies w.r.t. the Mean of systolic pressure (average of measured and estimated systolic pressures). See table II for details

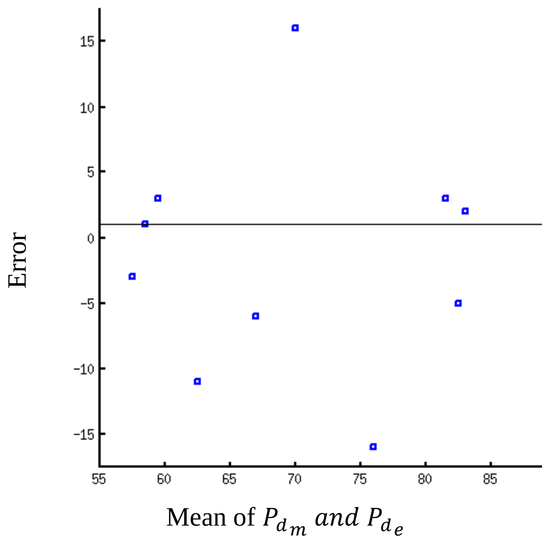

Figure 6: The plot shows how Error (Equation 8) varies w.r.t. the Mean of diastolic pressure (average of measured and estimated diastolic pressures). See table II for details

The error is defined as the difference between diastolic pressures estimated and measured as described in equation 7-8. Here the subscript "e" is used for the estimated values and "m" is used for the measured values of BP.

$$Error = Ps_e - Ps_m \quad (7)$$
$$Error = Pd_e - Pd_m \quad (8)$$

RMSE (root mean squared error) for P_s and P_d are 11 and 6 mmHg respectively. The deviation is mainly contributed by an outlier data error of 27 mmHg. The standard deviation of P_s and P_d are 12 and 6 mmHg respectively. The individual values of actual and estimated pressures are given in Table 2

Table II: Ground truth and estimated values of BP. Systolic and diastolic blood pressure is given for both estimated and ground truth cases. The ground truth values were measured by using a calibrated sphygmomanometer

SL No.	Ground truth		Estimated	
	Ps_m	Pd_m	Ps_e	Pd_e
1	112	62	118	78
2	120	60	110	87
3	113	58	110	61
4	120	80	118	83
5	124	82	117	84
6	120	68	123	57
7	109	70	104	64
8	105	85	110	80
9	106	59	116	56
10	105	84	113	68
11	122	58	118	59

IV. CONCLUSION

A constitutive model and displacement signal based approach to estimate blood pressure has been proposed and validated in this paper. The method is validated using a bland-altman plot (Figures 5-6), RMSE errors of which are 6 and 11mmHg respectively for systole and diastole. This plotting is used to validate methodologies in biomedical algorithms [15]. The neural network training algorithm uses 15% of the data for validation giving a cross correlation coefficient of 95% [fig 4c].

In future, this proposed method could be personalized to suite different physiological conditions using an appropriate distribution of the personal physiological characteristics. The use of displacement signal minimizes the damage to the skin by eliminating the need to remove the heat generated as in a PPG.

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