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A NEW PARADIGM ON MODEL-BASED PREDICTIVE ALGORITHM FOR OSCILLOMETRIC BLOOD PRESSURE MONITOR

Arpita Bhattacharjee[1] and Arup Ratan Ray[2]*

[2]Freelance.
[1,2]Bangalore, India.

***Corresponding Author: Arup Ratan Ray**

Freelance, Bangalore, India.

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ABSTRACT

An accurate estimation of systolic and diastolic pressure from oscillometric pressure signal has a great influence in health monitoring and clinical applications. This paper proposes a model based predictive algorithm comprising a predictive Volterra model, predictive statistical model and Chi Square test for the goodness of fit. Volterra models are developed from the ADC value of the oscillometric pressure signal data. Recursive least square filter is used to compute the Volterra kernels from input-output data. Local models based on Volterra model are created for individual systolic and diastolic group. Predictive statistical model is developed based on the variables like age, weight, diet, illness profile, geographic location etc. The accuracy of the model is improved using Chi Square goodness of fit test. Training and test data set can be used to create and test the model respectively.

KEYWORDS: Systolic and diastolic pressure, oscillometric pressure signal, Volterra model, Volterra kernel, recursive least square, Chi Square test.

1. INTRODUCTION

Blood pressure (BP) is a powerful, consistent, and independent indicator for cardiovascular diseases, stroke, renal diseases, and hypertensive retinopathy. The American Heart Association's[1] and other medical publications stress that the measurement of BP is important and critical for health monitoring of human beings.

Most of the BP monitoring devices, currently available in the market, have been developed based on oscillometric method. Oscillometric blood pressure monitoring device available in the market have an accuracy of ±3mmHg. A meta-analysis of 1 million patient shows that a 3–4 mmHg increase in systolic blood pressure translates into 20% higher stroke mortality and a 12% higher mortality from ischemic heart disease.[1] However, most of these devices give good accuracy in young healthy subjects, but they are less accurate in some subgroups such as older people due to various artery stiffness and people with different physiological diseases, e.g., pregnant women, arrhythmia, diabetics etc. Thus, the accurate detection of SP and DP by oscillometric method is still an open problem in biomedical engineering.

BP measurement includes two important parameters: systolic pressure (SP) and diastolic pressure (DP). SP is the highest value of pressure that occurs when the heart contracts and ejects the blood in to the arteries and DP is the lowest pressure value that occurs between each systole. Existing devices give valid estimates of mean arterial pressure (MAP), i.e., average pressure of an individual, but questionable estimates of SP and DP.

The challenges in accurate estimation of SP and DP are: 1) variations of measurement from Oscillometric BP monitor due to noisy environments, cuff dimensions, position of the arm, deflation rate etc. 2) inter- and intra-patient variation in physiological parameters due to patient physiological state, patient emotional state, activities, smoking, caffeine etc.[2,3] Thus, to avoid erroneous diagnosis and treatment we need to determine SP and DP in presence of measurement and inter- and intra-patient variability.

Numerous algorithms for oscillometric BP monitoring device have been developed so far. Two basic algorithms are fixed ratio and differential algorithm.[2,4-7] To estimate BP using fixed ratio algorithm, systolic ratio (SR) and diastolic ratio (DR) are calculated by dividing amplitude of the SP and DP by maximum amplitude of the cuff pressure i.e. MAP. The drawback of this method is that these fixed ratios cannot capture inter- and intra patient variability. In differential algorithm, BP is determined from the maximum and minimum positive slope of the oscillation envelope.

In order to improve the accuracy of SP and DP determination, Wang *et. al.* designed a model-based fuzzy logic control system by detecting the arterial

volume pulse.[8,9] Lin et al developed recursive weighted regression algorithm to reduce the interference in the oscillation amplitudes.[10] Thomas J. Dorsett developed an algorithm based on a Kalman filter to smooth the pulse amplitude data and predict the amplitude of the next pulse.[11] Forouzanfar et. al. have used the feed-forward and cascade-forward neural network designs for the determination of SP and DP.[12] Colak et. al. developed a neuro-fuzzy approach that uses the Principal Component Analysis (PCA) and fuzzy sets to determine the pressure profiles from the oscillometric waveforms.[13,14] These algorithms mostly give accurate results in young healthy subjects, but not in older people and patients with various diseases.

Accurate determination of SP and DP requires a model that can capture the physiological behaviour of young and older subjects and patients with different physiological parameters. A model based algorithm that can capture dynamic behaviour of subjects is more suitable for the accurate determination of SP and DP. Liu et. al. developed parametric model-based BP estimation methods based on physical modelling.[15] The determination of BP in various subjects is a nonlinear system. But the parametric models are not well suited for nonlinear systems. On the contrary, nonparametric models are mostly used for nonlinear systems. It is very difficult to identify a nonlinear system having different domain of operation using a global model. Thus, the effective way of identification of BP determination is to build multiple local models for several operating regimes.[16]

In the present paper, a nonparametric Volterra model based predictive algorithm is proposed. The raw signal of the oscillometric cuff pressure (CP) is to be collected for whole range of BP measurement. To eliminate the noise contained in the oscillometric CP, a band-pass filter is applied. Erroneous pulse created due to some external disturbances such as arm movement is removed. Error pulse is estimated by calculating heart rate (HR) and mean heart rate (MHR). Envelope is detected on the band-pass filter output. Features e.g., area of the envelope and maximum positive and negative slope are extracted. Local models based on Volterra model are created for individual systolic and diastolic group. Volterra kernels of the model are computed by recursive least square (RLS) algorithm. Finally, a predictive statistical model can be built based on different variables like age, weight, diet, illness profile, geographic location etc. Chi Square test is done to improve the accuracy of the model. Models have to be created with training data set and testing is to be done with test data set.

2. SYSTEM OVERVIEW

Currently most of the self-monitoring devices available in the market uses oscillometric technique for the measurement of blood pressure. In this technique, cuff is inflated to a maximum pressure value and the artery is blocked. Pressure is decreased gradually. The decrease in pressure inside the cuff is measured by a Pressure sensor.

The block diagram of the hardware device and flow chart for BP measurement is shown in Fig 1. A button is used in the hardware to control the operations of the complete device. Once the Start button is pushed, the device turns on the motor which inflates the cuff. The air will be pumped into the cuff until the pressure inside the cuff reaches 180 mmHg. After that, the motor will be stopped and the pressure will be released gradually at 3mmHg per second. The components of the hardware circuit are: MCU, driver circuit, pressure sensor, amplifier circuit and power supply board (PSB).

The MCU is the main component of the hardware device. It controls all the operations such as motor and valve control, A/D conversion. A software algorithm is embedded in the MCU that controls all the operation and also detects the SP and DP of an individual. The driver circuit drives motor and valve. Pressure sensor gives Voltage signal based on the differential pressure. As the Voltage signal from the pressure sensor is very low, an amplifier circuit is used to enhance the signal strength. Through ADC, MCU stores the Voltage signals obtained from the amplifier. PSB gives supply Voltage of ±5V to driver circuit and amplifier circuit. The measured BP is then displayed on LCD screen or in PC.

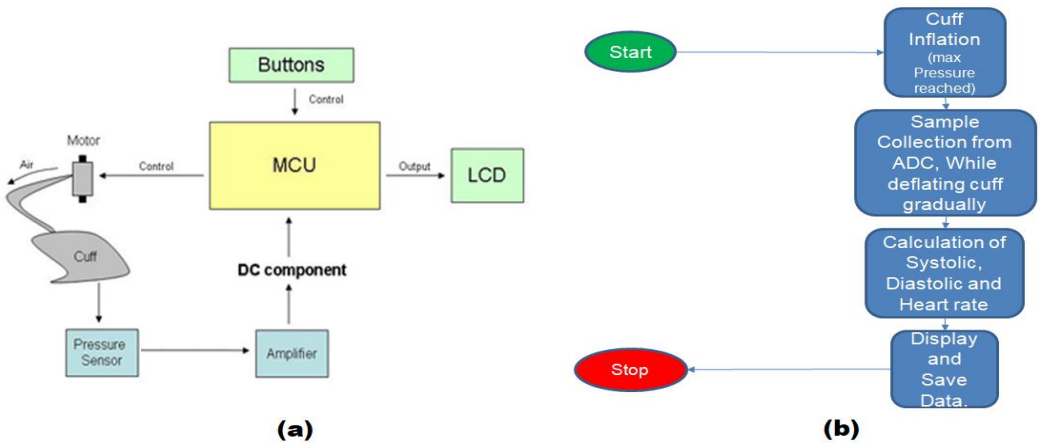


Fig 1: Block diagram of the hardware device and flow chart for oscillometric BP monitoring device.

A data set is collected from individual of different age group and gender simultaneously using oscillometric method and using auscultatory method. SP and DP measurement obtained from auscultatory method can be used for validation of the algorithm. An ADC output of the sampled oscillometric pressure signal data with marked SP and DP value obtained by auscultatory method for a random individual is shown in Fig 2.

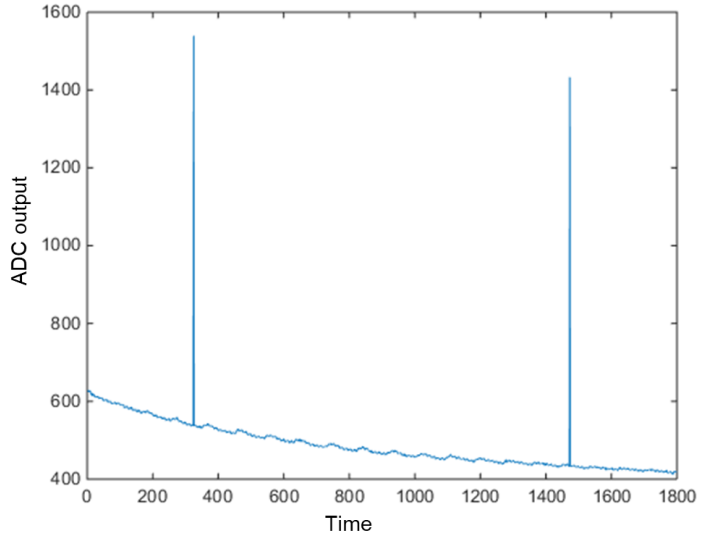


Fig 2: ADC output of oscillometric pressure signal with marked SP and DP obtained by auscultatory method.

3. DEVELOPMENT OF MODEL BASED PREDICTIVE ALGORITHM

Model based predictive algorithm can be developed from ADC value of the oscillometric pressure signal data. In this method, band pass filter is applied on the oscillometric pressure signal data. ADC and band pass filter output of oscillometric pressure signal data of Fig 2 is shown in Fig 3(a) and (b).

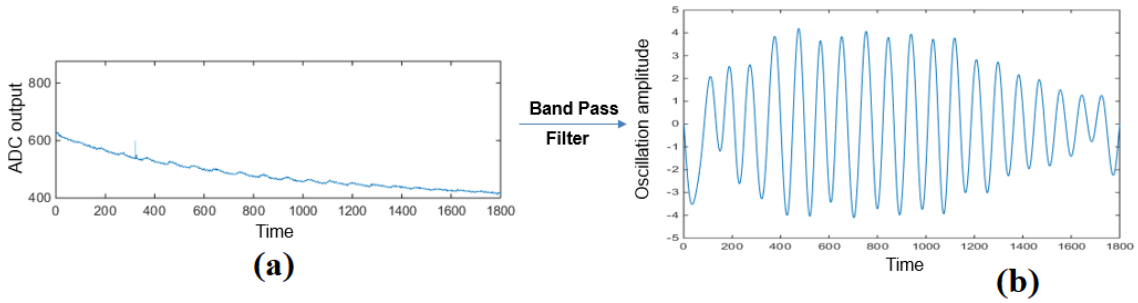


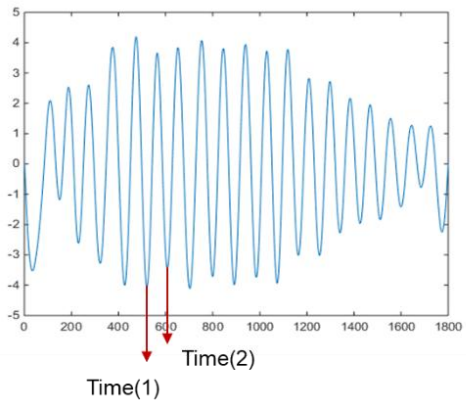
Fig 3: Oscillometric pressure signal (a) ADC output (b) output after applying band pass filter in ADC output.

If any erroneous pulse is present in the oscillations due to external disturbances, e.g., arm movement then it can be removed by an algorithm.[7] In this algorithm, HR and MHR is calculated using following equations:

$$HR = \frac{1}{Time(2) - Time(1)}$$

$$MHR = \frac{\sum HR}{No.\ of\ heart\ beats}$$

where, *Time*(2) and *Time*(1) is shown in the following figure:



Erroneous pulse is detected by applying the following condition:

Erroneous detection = { Positive if *HR* >130% of *MHR* or <70% of *MHR*; Negative otherwise }

Once erroneous pulse is removed, local models can be designed by grouping of individual SP and DP as follows:

Systolic	Diastolic
80-100	50-70
100-120	70-90
120-140	90-110
140-160	110-130
160-180	130-150
180-200	

The features are extracted from the envelope created by connecting peak value of each oscillation shown in Fig 4.

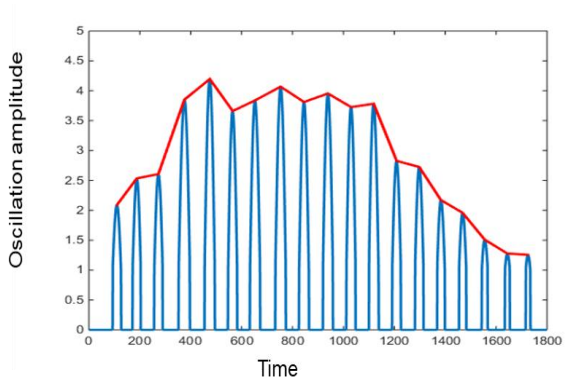


Fig 4: Envelope detection in band pass filter output.

The extracted features are: area under the envelope, maximum positive and negative slope of the envelope. For a sampled data of Fig 2, area under the envelope and maximum positive and negative slope are shown in Fig 5.

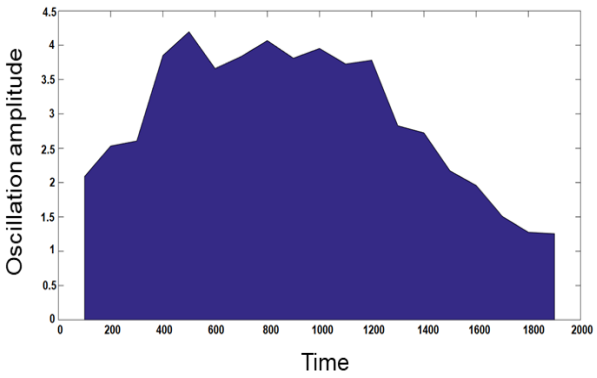


Fig 5: Area under the detected envelope of Fig 4.

The local models can be developed by taking the extracted features of the training data signal as input and SP and DP value obtained from auscultatory method as output. These local models are built for each variable like age, weight, diet, illness profile, geographic location etc. During testing detection of SP and DP value can be done using these local models.

A. Local Models: Implementation of Volterra model

The finite Volterra series up to second order kernel for muti-input single output (MISO) process is expressed as:

$$y(t) = g(0) + \sum_{i=1}^{m}\{\sum_{\tau=0}^{M-1} g_i^{(1)}(\tau)x_i(t-\tau)\} + \sum_{i=1}^{m}\{\sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1} g_{ii}^{(2)}(\tau_1,\tau_2)x_i(t-\tau_1)x_i(t-\tau_2) + \sum_{j=i+1}^{m}\sum_{\tau_1=0}^{M-1}\sum_{\tau_2=0}^{M-1} g_{ij}^{(2)}(\tau_1,\tau_2)x_i(t-\tau_1)x_j(t-\tau_2)\} \quad (1)$$

where, $y(t)$ is the estimated output at time instant t for a kernel memory length M and lag τ. $g^{(0)}$, $g^{(1)}$ and $g^{(2)}$ are the zero, first and second order Volterra kernels respectively, associated with the input $x(t)$.[17,18] The second order Volterra structure for the present two-input single output blood pressure detection local model is illustrated in Figure 6 and the overall output of the system is:

$$y(t) = g^{(0)} + g_1^{(1)} * x_1(t) + g_{11}^{(2)} * x_1(t) * x_1(t) + g_{12}^{(2)} * x_1(t) * x_2(t) + g_{22}^{(2)} * x_2(t) * x_2(t) + g_2^{(1)} * x_2(t) \quad (2)$$

where, the 'g' denotes the respective Volterra kernels and '*' denotes the convolutions. $y(t)$ is systolic/diastolic pressure. $x_1(t)$ and $x_2(t)$ are the extracted features i.e., area under the envelope and maximum positive and negative slope respectively. The structure of the second order Volterra model for blood pressure detection is shown in Fig 6.

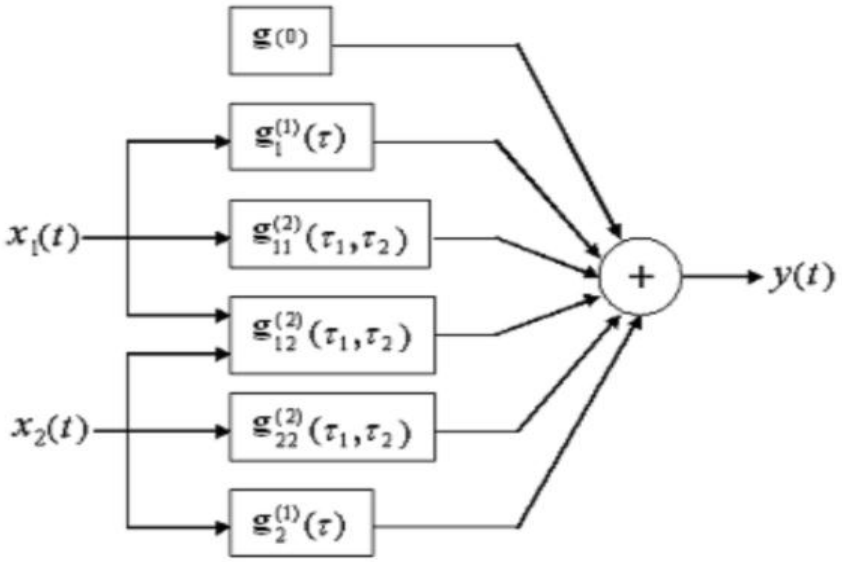


Fig. 6: Structure of second order Volterra model for blood pressure detection.

Volterra kernels are computed using recursive least square (RLS) algorithm.[17,18] These kernels are updated the same with new data set by minimizing the following cost function:

$$J(t)=\sum_{\tau=0}^{t}\lambda^{t-\tau}e^{2}(\tau)=\sum_{\tau=0}^{t}\lambda^{t-\tau}(y(\tau)-y'(\tau))^{2} \quad (3)$$

where $e(\tau)$ is the error signal, $y(\tau)$ is the patients' glucose output and $y'(\tau)$ is the estimated glucose output. λ is a 'forgetting factor' used to control the memory span of the adaptive filter. The structural diagram of the RLS filter algorithm is shown in Fig 7.

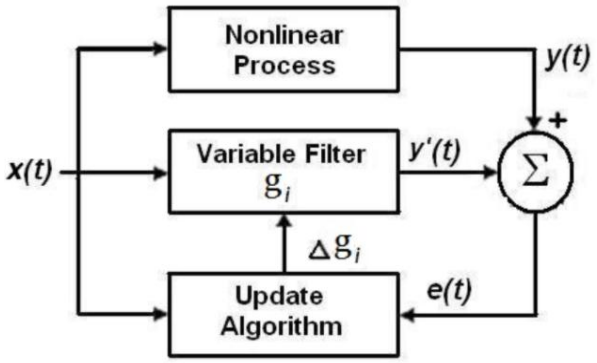


Fig 7: Structure of RLS filter algorithm.

The Volterra kernels are adapted according to the following steps:

1. Initialization: Define filter memory M; $G(0)=[0\,0\,..\,0]$; $P(0)=\delta * I$; where δ is a small positive constant;
2. Operations: for $t=1$ to number of iterations.

   a) Create the extended input vector:

   $$X(t)=[\,x_1^{(1)}\;\; x_{11}^{(2)}\;\; x_{12}^{(2)}\;\; x_{22}^{(2)}\; x_2^{(1)}\,] \quad \text{(for 2-input)}$$

   b) Compute the output: $y(t)=G(t-1)*X'(t)$

$$\text{where, } G=[\,g_1^{(1)}\;\; g_{11}^{(2)}\;\; g_{12}^{(2)}\;\; g_{22}^{(2)}\;\; g_2^{(1)}\,]$$

c) Compute the error: $e(t \mid t-1) = y(t) - y'(t)$

d) Compute the gain matrix: $G_g(t) = \frac{\lambda^{-1} P(t-1) G'(t-1)}{1 + \lambda^{-1} X(t) P(t-1) X'(t)}$

e) Update the filter vector: $G(t) = G(t-1) + e(t \mid t-1) * G_g'(t)$

f) Update the inverse autocorrelation matrix *P*:

$$P(t) = \lambda^{-1} P(t-1) - \lambda^{-1} G_g(t) X(t) P(t-1)$$

G represents the local model that can be first trained with the training data set and used for the detection of blood pressure.

4. STATISTICAL ANALYSIS BASED MACHINE LEARNING

Chi square test for the goodness of fit can further improve the algorithm by establishing whether the data fits a distribution from a certain population.[19] In other words, it indicates if the sample data represents the data that is expected to be found in the actual population.

$$\chi_c^2 = \sum \frac{(O_i - E_i)^2}{E_i} \quad (4)$$

O represents the Observed and *E* represents the Expected values.

The expected value would come from the predictive statistical model, which would be built by accumulating and analysing multiple data sets from actual measurements on subjects. The model will be built in such a way that the model will learn from further measurements and adapt the changes to make more accurate predictions.

The predictive statistical model could finally be an equation with different variables like age, weight, diet, illness profile, geographic location etc. The variables y_1, y_2, y_3… are the outputs of the local models (described in section 3) based on the input variables like age, weight, diet, illness profile, and geographic location etc. to the local models at the time of the BP measurement of the subject. The values of the multiplication factors a_1, a_2, a_3 … for the variables can be determined by solving the multivariate equation with actual large sample set measurements.

$y = a_1y_1 + a_2y_2 + a_3y_3 + \ldots\ldots\ldots\ldots\ldots + a_Ny_N$ (5)

Once the multiplication factors are determined, it could be stored in a lookup table, which will be adaptively improved by the machine, as more and more measurements are carried out. The Chi Square Goodness of Fit is evaluated for each of the measurements and the corresponding predicted values.

5. CONCLUSION

The algorithm and analytical approach presented in this paper to determine SP and DP using oscillometric method is a proposed improved solution to an open problem in biomedical engineering. We have developed a mathematical foundation, comprising of Volterra model, predictive statistical model and Chi Square test for the goodness of fit, to enable the estimation of SP and DP accurately. Local models i.e., the Volterra models are developed using recursive least square (RLS) algorithm. The present algorithm has a more personalised measurement approach as against the generalised measurement techniques used in the present-day Automated BP Monitoring Machines. Further experimentations are required to validate the above method. Future work will focus on more extensive study and experimental validation of the proposed approach in a large group of subjects.

Further development and incorporation of this algorithm into automated portable BP monitoring devices may lead to more reliability with respect to the accuracy of systolic and diastolic pressure readings obtained using oscillometric method and, in turn, lead to more accurate diagnosis based on the results using these devices.

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