Estimation of Blood Pressure from Non-invasive Data

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Abstract— **Blood pressure (BP) is one of the most important physiological parameter that can provide crucial information for health care. The widely used cuff based technology is not very convenient or comfortable as it occludes the blood flow in the arteries during the time of measurement. In the past, Phonocardiogram (PCG), Electrocardiogram (ECG) and Photoplethysmogram (PPG) signals have been used to predict BP values. In this paper, we propose to estimate blood pressure from PPG using Multi Task Gaussian Processes (MTGPs) and compare with Artificial Neural networks (ANNs). Both MTGPs and ANNs are evaluated on the clinical data obtained from MIMIC Database. The performance of the proposed method is found to be comparable or better than the existing methods of computing BP from non-invasive data.**

I. Introduction

In today's world, a lot of importance is given to personal healthcare. Due to infrequent monitoring, chronic hypertension often goes undetected which can be a cause for many diseases including kidney failure, heart attack and stroke. Invasive methods are known to measure blood pressure continuously and accurately but they might cause infection. The generally used non-invasive method is cuff-based which does not prove to be convenient for injured or older people. Cuff based technique occludes the flow of blood in arteries during blood pressure measurement and causes an unpleasant feeling and discomfort. Moreover, the cuff can sometimes cause underestimation of systolic blood pressure because of improper cuff size [1]. Therefore, there is an unmet need of non-invasive, cuff-less technique to accurately measure blood pressure.

Literature study shows that the vascular transit time [2], pulse transit time [3]-[5], pulse arrival time [6] and pulse wave velocity [7] can be used for non-invasive, cuff-less blood pressure estimation. Blood Pressure can be measured from the time difference between peaks of ECG and PPG, or from PCG and PPG, or from the two PPG signals. The idea of estimating BP from a single PPG signal was investigated in [8]-[11]. Authors have reported a linear correlation between BP and diastolic time obtained from PPG signal.

Apart from diastolic time, systolic time, $2/3$ and $1/2$ pulse amplitude width are also considered potential parameters for estimating BP. Many authors [3]-[10] have provided different coefficients to estimate BP from different features obtained from PPG signal, which give accurate results only on a specific set of data. Coefficients have to be adjusted for another set of inputs.

In order to remove this problem, a neural network has been employed in [11] which takes twenty one features of PPG signal as input and outputs systolic and diastolic blood pressure. In [5], it was already shown that neural networks provide better results than regression analysis in estimating the blood pressure from pulse transit time. In this paper, we propose to estimate the blood pressure using Multi Task Gaussian Processes and compare with neural network models with varying complexity. Data for training and testing are extracted from Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) [12] database.

II. Multi Task Gaussian Process Model

The Gaussian Process (GP) framework is a really handy tool for regression tasks in machine learning. Compared to other regression methods, the basic advantage with GPs is their ability to integrate prior knowledge like periodicity. We briefly describe the Single Task Gaussian Process (STGP) before moving to MTGPs. More details can be found in [16]. Let $\mathbf{x}_n = \{x_i | i = 1, ..., n\}$ and $\mathbf{y}_n = \{y_i | i = 1, ..., n\}$ be the training data and labels respectively. The objective is to learn a regression model $y = f(x) + \varepsilon$ where $f(x)$ is the latent function and $\varepsilon = \mathcal{N}(0, \sigma^2)$ a noise term. Noise term is included as the data are often noisy as well. The function f can be expressed as a probability distribution over functions,

$$y_n = f(x_n) \sim \mathcal{GP}(m(\mathbf{x_n}), k(\mathbf{x_n}, \mathbf{x'_n})) \tag{1}$$

where $m(\mathbf{x_n})$ is the mean function of the process and $k(\mathbf{x_n}, \mathbf{x'_n})$ is the covariance function which models the coupling between two values of $\mathbf{x_n}$. We can predict label y_* for an unknown data x_* given $\mathbf{x_n}$ and $\mathbf{y_n}$ by computing the conditional distribution $p(y_*|x_*, \mathbf{x_n}, \mathbf{y_n})$,

$$p(y_*|x_*, \mathbf{x_n}, \mathbf{y_n}) \sim \mathcal{N}(m_*, var_*) \tag{2}$$

Assuming mean function m to be zero, the mean and variance are given by

$$m_* = k(\mathbf{x_n}, x_*)^T k(\mathbf{x_n}, \mathbf{x_n})^{-1} \mathbf{y_n} \tag{3}$$

$$var_* = k(x_*, x_*) - k(\mathbf{x_n}, x_*)^T k(\mathbf{x_n}, \mathbf{x_n})^{-1} k(\mathbf{x_n}, x_*) \tag{4}$$

The covariance function helps us to include the prior knowledge of the time series that we wish to model. There exists a large class of covariance functions that we can use, described in detail in [16]. Most commonly used ones are squared exponential (SE), periodic (PER) and quasi-periodic (QP) covariance functions:

$$k_{SE}(r) = \theta_s^2 \exp\{-\frac{r^2}{2\theta_L^2}\} \tag{5}$$

$$k_{PER}(r) = \theta_s^2 \exp\{-\frac{\sin^2[(2\pi/\theta_P)r]}{2}\} \tag{6}$$

$$k_{QP}(r) = \theta_s^2 \exp\{-\frac{r^2}{2\theta_L^2}\} \exp\{-\frac{\sin^2[(2\pi/\theta_P)r]}{2}\} \tag{7}$$

where θ_S, θ_L and θ_P are hyperparameters which can be optimized by minimizing the negative log marginal likelihood $(-\log(p(\mathbf{y_n}|\mathbf{x_n})))$, $r = ||x - x'||$ denotes the Euclidean distance between two data.

Multi Task Gaussian Processes (MTGP) can model multiple correlated physiological time series simultaneously by learning correlation between multiple signals sampled at different frequencies and signal values available at different time stamps. They have been used in the analysis of physiological time series [15].

For MTGP, we analyse m tasks simultaneously using a single GP model. We assume that $\mathbf{X} = \{x_i^j | j = 1, ..., m, i = 1, ..., n^j\}$ and $\mathbf{Y} = \{y_i^j | j = 1, ..., m, i = 1, ..., n^j\}$ are the training indices and observations for m tasks, where task j has n^j number of training data. A label $l^j = j$ is added to specify the association of index x_i^j and observation y_i^j to task j.

In MTGP, we use two independent covariance functions to model the correlation between tasks as well as temporal behaviour of the tasks within a single GP.

$$k_{MTGP}(x, x', l, l') = k^t(x, x') \times k^c(l, l') \tag{8}$$

where k^c and k^t are the correlation and temporal covariance function between $\{x, l\}$ and $\{x', l'\}$ respectively.

The complete covariance matrix for all m tasks can be written as,

$$\mathbf{K}_{MTGP}(\mathbf{X}, \mathbf{l}, \theta_c, \theta_t) = \mathbf{K}_c(\mathbf{l}, \theta_c) \otimes \mathbf{K}_t(\mathbf{X}, \theta_t) \tag{9}$$

where $\otimes$ is the Kronecker product, $\mathbf{l} = \{j | j = 1, ..., m\}$, θ_c and θ_t are vectors containing hyperparameters for $\mathbf{K}_c$ and $\mathbf{K}_t$ respectively, $\mathbf{K}_c$ has a size of $m \times m$, $\mathbf{K}_t$ and $\mathbf{K}_{MTGP}$ has a size of $N \times N$ where $N = \sum_{j=1}^m n^j$. $\mathbf{K}_c$ is the correlation matrix which captures the correlation between different tasks while $\mathbf{K}_t$ captures the temporal covariance functions within a task.

Cholesky decomposition is used to construct a valid positive semidefinite covariance matrix $\mathbf{K}_c$ [17].

$$\mathbf{K}_c = LL_T, L = \begin{bmatrix} \theta_c^1 & 0 & \dots & 0 \\ \theta_c^2 & \theta_c^2 & \dots & 0 \\ \vdots & \ddots & & \\ \theta_c^{k-m+1} & \theta_c^{k-m+2} & \dots & \theta_c^k \end{bmatrix} \tag{10}$$

where $k = \sum_{i=1}^m i$ is the number of correlation hyperparameters. For uncorrelated tasks $\mathbf{K}_c$ will be an identity matrix.

The covariance function used is a combination of Matern kernel, squared exponential and periodic covariance function.

$$k(x, x') = k_M(x, x') + k_{QP}(x, x') \tag{11}$$

$$k_M(x, x') = \theta_m\{1 + \frac{\sqrt{3}r}{\theta_d}\} \exp\{-\frac{\sqrt{3}r}{\theta_d}\} \tag{12}$$

$$k_{QP}(x, x') = \theta_s^2 \exp\{-\frac{r^2}{2\theta_L^2}\} \exp\{-\frac{\sin^2[(2\pi/\theta_P)r]}{2}\} \tag{13}$$

where θ_m, θ_d, θ_s, θ_L and θ_P are hyperparameters which are optimized by minimizing the negative log of marginal likelihood, $r = ||x - x'||$ is the Euclidean distance between x and x'. Similar to STGPs, prediction on the test data $\{x_*, l_*\}$ can be made by computing the conditional probability $p(y_*|x_*, l_*, \mathbf{X}, \mathbf{Y}, \mathbf{l})$.

III. Experiments

A. Data

Freely available MIMIC database [12] is used as the source for the PPG signal and corresponding BP values. It contains various physiological signals captured from thousands of people. Most of them include ECG, PPG, BP and many other signals which were recorded simultaneously at a sampling frequency of 125 Hz. Besides healthy people, the MIMIC database also contains signals from elderly people, people with hypertension and other diseases. Only the signals with both PPG and BP are extracted from this database, figure 1 shows such an example. We select a random subset of 100 patients from this dataset for our evaluation.

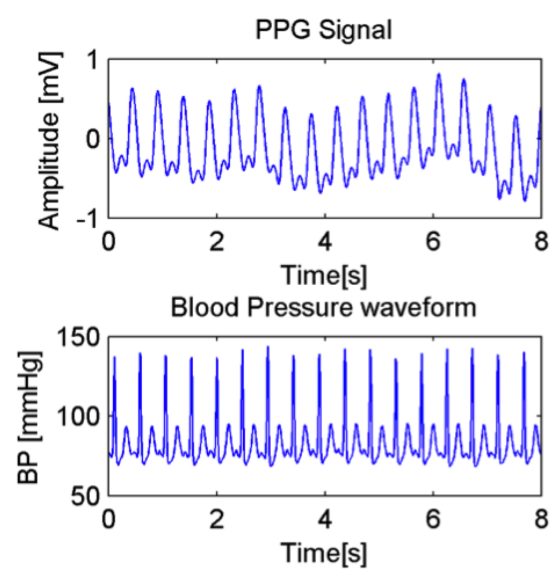

Fig. 1. Sample PPG signal and corresponding BP waveform from MIMIC database

B. Preprocessing

A Photoplethsmograph (PPG) reflects the change in volume of the vascular blood with each cardiac cycle. Vital components of this signal include amplitude of the signal, width of systole and diastole, among other measurements. Amplitude of PPG signal varies due to moving artifacts at the time of acquisition of the signal. So, the amplitude cannot be used as a feature for the estimation of BP. Preprocessing is required to remove the base line wandering, physiological noise, motion artifacts and optical measurement noise in the PPG signal. Zero phase filtering is done with a $2nd$ order Butterworth high pass IIR filter (cutoff frequency: 1 Hz).

The output of a FIR filter consists some group delay. Hence, IIR filter is used because of its advantage of sharp transition with a small number of coefficients but it has a non-linear phase response which can distort the meaningful components of the PPG signal. Zero phase filtering is used to overcome this. The results of a zero phase filtering has the following advantages:

- Zero phase distortion
- Squared magnitude of original filter transfer function
- Order gets doubled

Figure 2 shows the filtered signal along with the raw input.

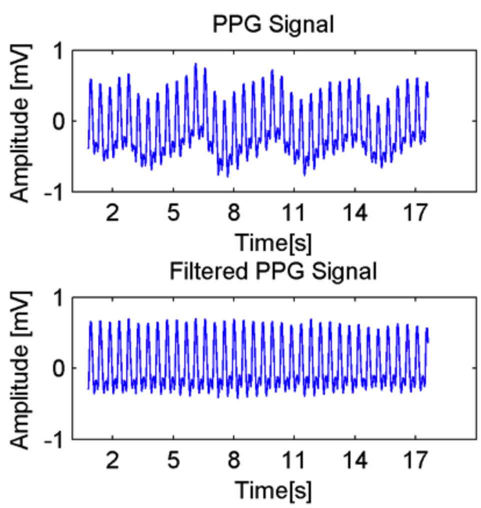

Fig. 2. Top: Raw PPG signal, Bottom: Filtered PPG signal

C. Feature Extraction

Several features can be extracted from PPG signal to estimate blood pressure. Diastolic time, systolic time, width of ⅔ and ½ pulse amplitude are used in [9] while cardiac period, peak height and peak width at 10% of pulse height in [13]. In order to increase the accuracy of estimated BP and to extract the maximum information from PPG signal, several parameters are considered.

A total of 10 parameters are extracted. These set of parameters provide accurate representation of a cardiac cycle and can estimate the blood pressure correctly.

1) Systolic upstroke time
2) Diastolic time

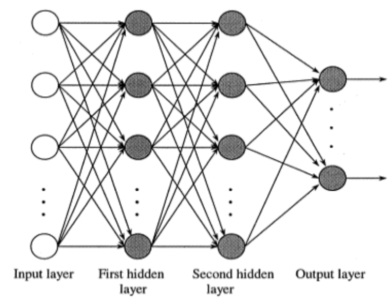

Fig. 3. NN architecture for BP estimation

3) Cardiac Period
4) Ratio of diastolic to systolic time
5) Diastolic width at ½ of pulse height
6) Width at ½ of pulse height
7) Ratio of diastolic to systolic time at ½ of pulse height
8) Diastolic width at ⅔ of pulse height
9) Width at ⅔ of pulse height
10) Ratio of diastolic to systolic time at ⅔ of pulse height

The reference value of SBP and DBP is calculated as the maximum and minimum value of the blood pressure waveform in a cardiac cycle, respectively.

D. MTGP Model

To construct the MTGP, five tasks are considered – systolic blood pressure, diastolic blood pressure, systolic upstroke time, diastolic time and cardiac period. The datasets of each patient are randomly partitioned in 75%:25% into training and test sets respectively. Patient-specific MTGP is constructed using the training set for each patient, where 5-fold cross validation is used to report the final accuracy.

E. Neural Network

A multilayer feed-forward back propagation neural network (NN) with N inputs, two hidden layers and two outputs is used to estimate systolic and diastolic blood pressure. Sigmoid function is used as the activation function and Levenberg-Marquardt algorithm is used for learning the weights of the neurons in the NN. Figure 3 shows the neural network architecture.

Following experiments were carried out with varying number of features of PPG signal in the input layer of neural network to compare the performance of prior works.

- **NN1**: Linear regression is performed with diastolic time because [9] shows that it has the highest correlation with diastolic and systolic blood pressure as compared to other features.
- **NN3**: Three features – systolic upstroke time, diastolic time and cardiac period are used in the input layer of NN.
- **NN4**: Ratio of diastolic to systolic upstroke time, systolic time, diastolic time and cardiac period are used as input neurons.
- **NN10**: All the 10 features are used as input to the neural network.

We construct patient specific neural network using training set of each patient, where 5 fold cross validation is used to report the final accuracy.

IV. Results

The absolute error e is calculated for every heart beat as:

$$e = |BP_{est} - BP| \tag{14}$$

where BP_{est} is the estimated SBP or DBP using NN or MTGP, and BP is obtained from MIMIC database reference value.

Table I shows the performance of the experiments mentioned above on the test set, presented as mean and standard deviation of absolute error e between the reference and estimated values. Clearly, Multi Task Gaussian process performs better than other models.

TABLE I
Performance of MTGP and NN

Method	**Systolic BP**	**Diastolic BP**
	e[mmHg]	e[mmHg]
NN1	7.73 ± 9.80	5.72 ± 7.91
NN3	4.75 ± 7.39	3.95 ± 7.31
NN4	4.81 ± 7.39	5.07 ± 7.63
NN10	3.91 ± 5.39	3.34 ± 5.67
MTGP	$\mathbf{1.12 \pm 1.06}$	$\mathbf{0.82 \pm 0.81}$

TABLE II
Comparison of different non-invasive methods

Method	**Systolic BP**	**Diastolic BP**
	e[mmHg]	e[mmHg]
VTT Method[2]	4.42 ± 5.99	3.57 ± 4.50
21 feature NN[11]	3.80 ± 3.46	2.21 ± 2.09
MTGP	$\mathbf{1.12 \pm 1.06}$	$\mathbf{0.82 \pm 0.81}$

Table II shows the comparison of other non-invasive methods used for estimation of blood pressure. MTGP performs better than the Vascular Transit Time (VTT) method used in [2] and the 21 feature Neural Network Model [11].

According to the American National Standards of Association for the Advancement of Medical Instrumentation [14], the absolute mean error in blood pressure measurement must be less than 5 mmHg and standard deviation must be less than 8 mmHg. Results of our experiment (except NN1 i.e. Linear Regression) clearly satisfies this standard requirement.

V. Conclusions

In this paper, blood pressure is estimated from features of Photoplethysmograph (PPG) using Multi Task Gaussian Processes and Neural Network (NN). Training and test data used for both the methods are the same. Different number of features have been used as input to the neural network. In MTGP, five tasks have been included - systolic and diastolic BP, and three features from PPG signal whose correlation are found higher than other features. Both the methods are evaluated on data of 100 patients extracted from MIMIC database. The obtained results also fulfill the standard requirements of the American National Standards of Association for the Advancement of Medical Instrumentation. MTGP gives better results in comparison with the mentioned neural network models and also the other non-invasive techniques used for BP estimation [2], [11].

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