Cuffless and Continuous Blood Pressure Estimation From PPG Signals Using Recurrent Neural Networks

Chadi El Hajj and Panayiotis A. Kyriacou

Abstract— **This paper proposes cuffless and continuous blood pressure estimation utilising Photoplethysmography (PPG) signals and state of the art recurrent network models, namely, Long Short Term Memory and Gated Recurrent Units. The models were validated on wide range of varying blood pressure and PPG signals acquired from the Multiparameter Intelligent Monitoring in Intensive Care database. Many features were extracted from the PPG waveform and several machine learning techniques were employed in an attempt to eliminate collinearity and reduce the size of input feature vector. Consequently, the most effective features for blood pressure estimation were selected. Experimental results show that the accuracy of the proposed methods outperform traditional models applied in the literature. The results satisfy the American National Standards of the Association for the Advancement of Medical Instrumentation.**

I. INTRODUCTION

High blood pressure or hypertension is a key factor for a number of life threatening diseases, such as cardiovascular diseases (CVDs), and chronic kidney diseases [1]. According to 2018's world health statistics report published by the World Health Organisation, approximately 17.9 million deaths worldwide were caused by CVDs in 2016 [2].

Blood pressure (BP) is an important physiological parameter providing information about the cardiac output, blood vessel elasticity, and physiological variations which are essential for physicians for assessing patients' circulatory system conditions. The normal BP range for adults are considered to be 90-129 mmHg for Systolic BP (SBP), and 60-84 mmHg for Diastolic BP (DBP). SBP and DBP values higher than this range indicate hypertension. Hypertension adds more strain on the blood vessels which can damage the internal organs of the human body leading to strokes, heart diseases, and kidney failures in the case of chronic hypertension. Moreover, for hypertensive patients, BP can fluctuate over time [3], and the changes in the SBP and DBP may occur rapidly due to a number of different factors, such as physical activity, stress, food, and emotions. Therefore, regular and continuous BP monitoring is desired for early diagnosis and treatment of hypertension so that further complications maybe be avoided.

The traditional BP measurement techniques in clinical practice are typically invasive or cuff-based. The invasive method can only be achieved via arterial catheterization. This method is considered to be the most accurate and provides continuous BP measurement values in real time for every cardiac cycle. Nonetheless, its application is limited to hospitals and can be painful. The most commonly used BP measurement devices are mainly based on oscillometric [4], and auscultatory [5] methods. These methods provide SBP and DBP values without any obvious risks. However, BP measurement using these devices is discontinuous and cuff-based, which is inconvenient and uncomfortable for patients due to repeated cuff inflation and deflation.

There has been considerable effort to develop cuffless BP measurement methods over the past decades, particularly using PPG sensors due to its simplicity and cuffless nature. Pulse Transit Time (PTT) has been known to be inversely correlated to BP [1], and can be measured using two distant PPG sensors located on the body. PTT is defined as the time taken by the pressure wave to travel between two arterial sites. Pulse Arrival Time (PAT) [1] is another approach that has been investigated. PAT is the time needed for the pulse wave generated by the heart to travel to a peripheral site e.g. fingers, toe, earls etc. PAT is measured using one PPG sensor and one Electrocardiogram (ECG) sensor. These techniques rely on a complicated arterial wave propagation models and face several practical challenges, such as the need for two measurement sensors, and frequent calibration due to varying physiological parameters between individuals [7].

More recently, with the rise of Machine Learning (ML), several studies have combined PTT and PAT parameters with many morphological features extracted from the PPG signals. These features describe the characteristics of the PPG waveform and have been found to be correlated to BP [6]. PTT or PAT parameter combined with PPG features along with machine learning models are able to provide better BP estimation accuracy [7], [8], as opposed to PTT or PAT only models [9], [10].

On the other hand, optical BP measurements using only PPG signals, has also attracted a lot of attention [11]–[15] due to its simplicity. This approach is able to provide cuffless and continuous BP estimation using features extracted from the waveform and the application of machine learning. Teng and Zhang [11] investigated the relationship between BP and PPG features using a linear regression model. Four features were extracted from the PPG as potential BP indicators. Their model was validated on a small dataset of 15 healthy subjects. This study reported promising results for cuffless SBP and DBP estimation. However, the relationship between BP and PPG pulse duration is not always linear [12] and this dataset does not well represent the general population. Non-linear classical ML models have also been tested including Support Vector Machine (SVM) and Regression Tree [15]. However, all the aforementioned models share one disadvan-

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tage, that is, they require two separate estimation models, one for each objective i.e. SBP and DBP. However, SBP and DBP are strongly correlated [3], and therefore, their estimation accuracy can be improved by learning shared representation using one model architecture. In Kurylyak et al [12], 21 temporal PPG features were extracted and evaluated on a feedforward neural network. The dataset used in this experiment is the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) database [16]. This database provides a wide representation of possible PPG signals and their corresponding BP values allowing for linear and non-linear models to be investigated. Their study produced acceptable results for cuffless and continuous BP estimation.

All the previously discussed ML and neural network models do not take into account the time domain variation in the extracted PPG features. The BP estimation accuracy can be further enhanced using recurrent neural networks that can model relevant PPG features, as well as their variation with respect to time.

In order to overcome these challenges, this paper proposes new methods for non-invasive cuffless BP estimation from PPG signals, using Long Short Term Memory (LSTM) and Gated Recurrent Units (GRU) networks. In [3], [17], LSTM networks were employed for estimating BP values using the PTT approach. Their results were superior to all the previously published PTT studies, suggesting that modelling the time domain variation for the input features would significantly improve BP estimation accuracy. Additionally, to the best of our knowledge, the GRU model has never been applied for BP prediction tasks in the literature.

This paper is organised as follows: section II presents a general overview of the data source, data pre-processing and feature extraction as well as introducing the models. Section III presents the results and analysis and section IV concludes the paper.

II. Methodology

A. Dataset description

The PPG and BP signals used in this study are derived from the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC II) [16]. This database is open source and widely used in research for BP estimation as it provides a wide variety of all possible PPG signals and reference to invasive BP signals from a diverse demographic. It contains thousands of vital physiological signals such as ECG, PPG, BP, and respiration etc. All signals are recorded simultaneously, and sampled at 125Hz. For this study, PPG and BP signals were acquired from 500 record files, each record is a collection of signals recorded from a patient.

B. Data pre-processing

Signal processing is crucial since accurate extraction of the PPG features from the original signals is essential towards building a reliable and well generalised model. A large number of PPG and BP signals provided by the MIMIC II database contain irregular and distorted segments. In order to effectively extract PPG features, the following pre-processing steps were preformed:

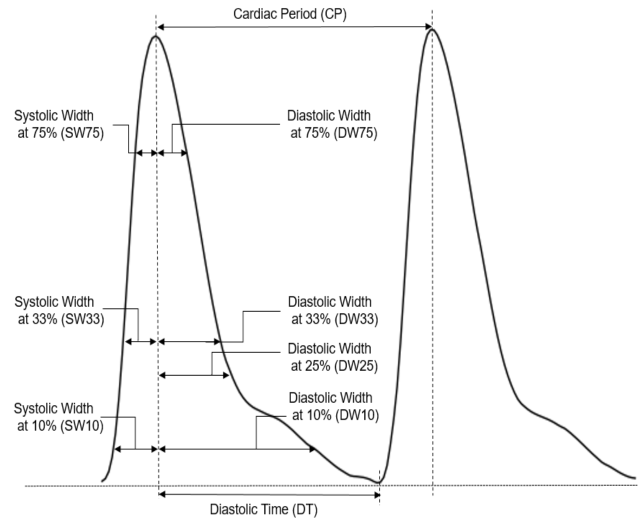


Fig. 1: Temporal PPG feature characteristics

- PPG signals were filtered and baseline wandering were removed
- Irregular, and distorted signal segments were removed
- Segments with abnormal heart rate and BP values were also removed
- PPG and BP signals were aligned
- PPG signals were normalised to a range of [0,1] using the min-max normalisation method

Following these steps, all PPG and their corresponding BP signals were segmented into 3 and 7 seconds frames which amounted to over 21000 and 9000 segments, respectively. The resulting datasets are later used as input for multiple linear regression model and neural network models.

C. Feature extraction

Several PPG features were proposed in the literature as possible effective indicators for BP estimation. Both time domain based features [11], [12], [14], [15], as well as frequency domain based features [13] have been tested. Time domain based features are the most commonly used in research. These features are mainly derived from the PPG and its first two derivatives. The main challenge that may arise in this procedure is that PPG waveform varies between individuals and can be affected by drugs, diseases, age, etc [3]. Consequently, some characteristic points that are essential for extracting a number of features may not be visible in all signals, such as dicrotic notch. For this study, the 21 PPG features presented in Kurylyak et al [12], in addition to pulse area under the PPG curve, were originally selected as possible feature pool for BP estimation. These features or a combination of them, are widely used in the literature and yield acceptable results. In an effort to further enhance the model estimation precision whilst at the same time reducing reducing its input vector dimension, only the most effective features have been selected. Several machine learning tools have been employed to investigate the impact of each feature on the output target:

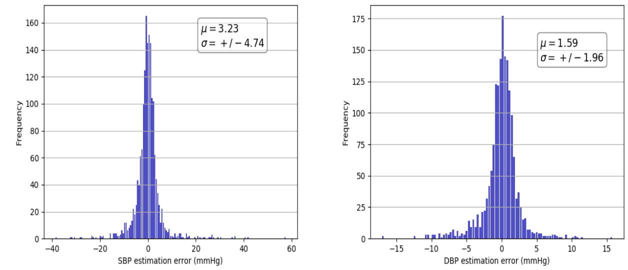
- Pearson's Correlation: measures the linearity between the features and reference BP
- Random forest feature importance: selects features with the highest influence on the estimation target using a fitted random forest regression model
- Recursive feature elimination: fits a regression model and tries to eliminate collinearity, by recursively removing a small number of features with the weakest impact on the estimation, until it reaches the specified number of features
- Sequential forward selection: starts with no features and sequentially adds only features that effectively improve the model performance till the addition of new features do not enhance the model accuracy.

The above mentioned techniques have been applied separately on the 22 feature vector. The results were analysed and only 7 features were selected. These features were common output of the feature selection methods corresponding to features with the highest impact on the BP estimation. The features used in this study are presented in Fig. 1, namely, CP, DT, DW10/SW10, DW25, SW33+DW33, DW75 and SW75+DW75. All extracted features were then normalised together using the min-max normalisation method to scale down all feature values to a range of [0,1] to suppress the effect of outliers that may exist in the dataset. The SBP and DBP values were extracted from the BP signals and correspond to the peak and far right end-diastole value, respectively. Two datasets were created afterwards, one containing 3 seconds segments which will constitute the input vector for the multi-linear regression model, and the other contains 7 seconds segments which are used as an input vector to the neural network models.

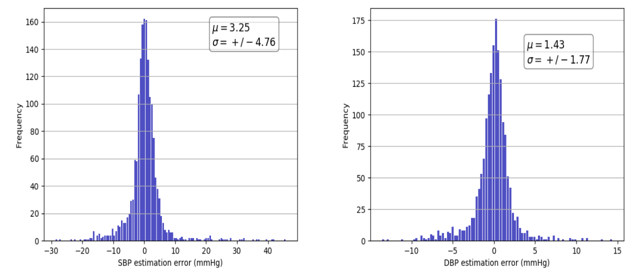
D. Machine learning models

As mentioned previously, the PPG signals differ between individuals due to varies factors such as age, gender, medications, diseases and other influences. Fortunately, the MIMIC database contains wide range of samples collected from a diverse population. Therefore, it provides an opportunity to evaluate the relationship between the PPG features and BP with linear and non-linear models, as well as study the effectiveness of modelling the temporal variation in the extracted PPG features on BP estimation. For validating the performance of these models, the dataset was partitioned into 60% train, 20% validation and 20% test sets. The evaluation metrics adopted for this study are the mean absolute error (MAE) and the standard deviation (STD) of the estimated error.

The main goal of this paper is to overcome the shortcomings of the traditional ML methods that are not best suited for time series tasks. Therefore, to take into consideration the complexity of the problem and the unclear relationship between the PPG features and BP, this paper proposes two non-linear recurrent neural network models, namely, LSTM and GRU. Both models provide competitive performance,



(a) LSTM



(b) GRU

Fig. 2: Histogram of error difference between the reference and estimated values for (a) LSTM and (b) GRU

and have been proven to be very effective and efficient in processing time series data. Moreover, in order to allow comparison to be made between traditional models and the proposed ones, multi-linear regression (MLR) and multilayer feedforward neural network were also evaluated on the 7 selected PPG features. The following describes the three neural network architectures:

- Feedforward neural network (NN): this model is a simple network with a feedforward (non-recurrent) connections, that is capable of approximating virtually any non-linear function with a finite number of neurons using a single layer. A grid search was performed with varying number of neurons, hidden layers and learning rate. The final optimised network consists 3 hidden hidden layers; 70, 100 and 150 neuron in each consecutive layer, respectively.
- Long Short Term Memory (LSTM): is the state of the art network for processing sequential time domain data. It was established specifically to overcome the vanishing gradient problem associated with long term predictions. The optimised LSTM model consists of two hidden layers, 64 and 512, in the first and second layer, respectively.
- Gated Recurrent Units (GRU): is a variation of the LSTM with competitive performance. This network is somewhat less computationally expensive then the LSTM. The best model after a grid search consists of three hidden layer, 128, 256 and 512 neurons in each consecutive layer respectively.

The learning algorithm used for training the above mentioned neural network models is Adam optimiser with back-propagation. The objective/cost function to minimise is the mean squared error. The estimation precision was assessed by the test set accuracy using MAE and STD.

III. Results

Experimental results for the models discussed in the previous section are presented in Table I. The evaluation metric follows the standard requirement set by the American National Standards of the Association for the Advancement of Medical Instrumentation (AAMI). According to AAMI the MAE and STD of non-invasive BP estimation should not exceed 5 ± 8 mmHg from a reference BP evaluated on 85 subjects [18].

TABLE I: Performance of varies BP estimation methods.

	SBP		DBP	
Models	MAE	± STD	MAE	± STD
MLR	12.14	7.37	4.54	3.57
NN	4.23	4.78	2.37	2.26
LSTM	3.23	4.74	1.59	1.96
GRU	3.25	4.76	1.43	1.77

Table I shows that the multilinear regression model is incapable of estimating SBP values and produced poor results for DBP compared to all other non-linear models. Consequently, it failed to capture the relationship between PPG features and BP on this diverse dataset. On the other hand, the results for all the neural network models were very promising and satisfied the AAMI standards. It is evident from the performance results, that the LSTM and GRU outperformed both the linear model and the non-recurrent feedforward neural network by a good margin. In particular, Fig. 2 shows the histogram of error for LSTM and GRU. The error estimation for both SBP and DBP are normally distributed around the mean with a relatively small standard deviation. Most of the error values are below $\pm$10mmHg for the SBP and $\pm$5mmHg for the DBP. This proves that modelling the time domain variation in the extracted PPG features is important and can further enhance the BP estimation accuracy. It also demonstrates the capability of the proposed models in describing the non-linear relationship between the extracted features and BP.

IV. Conclusion

This paper proposed continuous BP estimation models based on the PPG approach without ECG signals. Signal pre-processing steps were preformed followed by several feature elimination techniques to reduce the collinearity and improve the estimation accuracy. Seven PPG features were selected as possible BP estimators. The LSTM and GRU achieved a higher accuracy compared to traditional models, while satisfying the AAMI requirement for non-invasive BP estimation. The results can be further improved by increasing the size of the dataset, and optimising the input feature set to include information describing arterial stiffness, age, gender, height and other influences that affect BP.

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