TEXAS A&M UNIVERSITY

MACHINE LEARNING WITH NETWORKS

ECEN 765

Project Proposal

Cuff-less Blood Pressure Estimation using Regression Model based on Pulse Transit Time

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PURPOSE:

The purpose of this proposal is to request the approval for my course project about cuff-less blood pressure estimation using regression model based on pulse transit time method, which is suitable for wearable devices.

SUMMARY:

Blood pressure is an important risk factor for cardiovascular diseases. Pulse transit time (PTT) is a promising method that can allow continuous monitoring of blood pressure using wearable devices instead of the obtrusive conventional method, which is based on a bulky cuff. PTT is defined as the time taken by the pressure pulse to travel from the heart to specific point in the body through the arteries. In this project, blood pressure will be estimated using different regression models with several features extracted from electrocardiogram (ECG) and photoplethysmography (PPG) signals based on PTT. The dataset that will be used in this project is available online and it includes many recordings of simultaneous ECG, PPG and BP signals collected from patients in ICU. Several features will be tested to use the most effective features for blood pressure estimation. Performance comparison will be done among several regression models such as regularized linear regression, support vector regression and adaptive boosting. In addition, the results will be compared with published work, which uses the same dataset. A project schedule was proposed to finish the project within 10 weeks through three milestones.

INTRODUCTION AND MOTIVATION:

Cardiovascular diseases are the most common ailments in the world. About 30 million people suffer from cardiovascular diseases in the United States. Monitoring blood pressure (BP) is an essential method that physicians rely on to diagnose cardiovascular diseases. Continuous blood pressure monitoring is very important because it provides comprehensive information about the changes of blood pressure between different daily activities and from day to day, which results in a better diagnosis of cardiovascular diseases. The traditional method of measuring blood pressure depends on an inflated cuff, which is obtrusive and uncomfortable for the patient. Using the cuff limits the number of blood pressure measurements for few times per day, which can give inaccurate results due to temporary changes in blood pressure according to daily activates and patient’s stress. Furthermore, the cuff has big size, which makes this method not suitable for wearable devices. Pulse transit time (PTT) is a prominent method to measure blood pressure through small sensors that can be integrated into a wearable device, which enables the continuous monitoring of blood pressure.

Several research studies showed that blood pressure is highly correlated with PTT, which is the time taken by the blood pressure pulse to travel from the heart to the rest of the body [1]. The PTT can be measured using the electrocardiogram (ECG) and photoplethysmography (PPG) signals. The ECG signal is measured using three electrodes attached to the chest, which captures the electrical activity of the heart, while the PPG signal is measured from an optical sensor placed on the finger to capture the volume of the blood at this site. The PTT can be measured as the time delay between the R-peak of the ECG signal and the maximum slope point of the PPG signal as shown in Fig. 1.

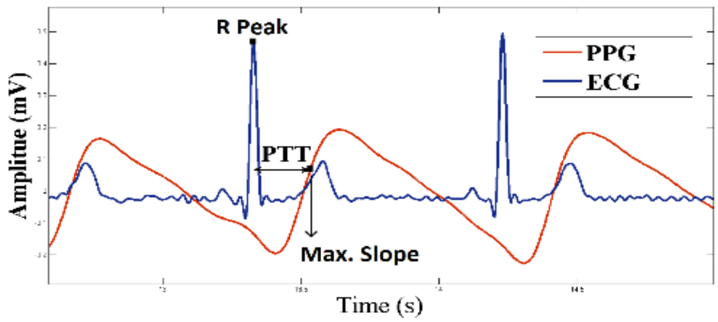

Fig. 1. PTT estimation using ECG and PPG waveforms.

The objective of this project is to use the PTT in addition to other features extracted from the ECG and PPG signals to predict the systolic blood pressure (SBP), diastolic blood pressure (DBP) and the mean arterial pressure (MAP), which are the maximum, minimum and average of BP. The BP will be predicted at each cardiac cycle based on a number of features extracted from the same cycle. In addition to the PTT, there are other several useful features, which are correlated to blood pressure such as the amplitude and the slope of the PPG main peak. Beside the main peak of the PPG signal, there is another smaller peak within the cardiac cycle, which represents the blood reflection in the arteries. The time difference between these two peaks is also considered a useful feature of BP. Furthermore, the first and second derivative of the PPG signal may be used to extract additional useful features. In this project, all these features will be examined in order to determine the most effective features for BP estimation.

The PPG sensor can be easily implemented into a wrist-watch as can be found in many commercial products such as Apple and Fitbit watches for heart rate tracking. The ECG sensor is more difficult to be implemented in wearable devices because it requires two electrodes at both sides of the heart. However, there are several other alternatives to measure PTT which are more suitable for wearable devices. One of these alternatives is studied in my current research project, which focuses on measuring PTT between two bio-impedance sensors on the wrist, which can be integrated into a wrist-watch [2, 3]. Bio-impedance sensor is an electrical method to measure blood volume similar to the PPG signal. Bio-impedance sensors are lower cost, lower power and easier to be integrated into a small area compared to the optical PPG sensors. Therefore, this course project is tightly related to my research and it will be very useful to my work. In addition, I have good background and knowledge about the ECG and PPG signals, which will help me to understand the major factors that affect the BP predictions.

METHODS:

The dataset "Cuff-Less Blood Pressure Estimation Dataset" from www.kaggle.com will be used in this project [4]. The dataset was uploaded recently from 5 months, and it includes 500 recordings of ECG, PPG, and invasive arterial BP. All the signals are simultaneously sampled at 125 Hz from patients in intensive care unit (ICU) of the Beth Israel Deaconess Medical Center between 2001 and 2012.

There are two publications, which estimated BP using this dataset as shown in [5, 6]. In [5], BP was estimated using several features extracted from ECG and PPG signal such as:

- PTT between the ECG signal and the peak, foot and maximum slope of the PPG signal

- Heart rate
- Ratio of diastolic peak to the systolic peak of the PPG signal
- Maximum slope of the PPG signal
- Time delay between the peaks of the PPG

This paper used the following regression models to estimate BP:

- Regularized Linear Regression Model
- Neural Networks Regression Model
- SVM Regression Model

In this paper, the results of these models were compared together by calculating the mean absolute error (MAE) and the standard deviation (STD) of estimation errors for SBP, DBP, and MAP.

A more comprehensive study was done using this dataset in [6] by comparing additional regression models such as:

- Decision Tree Regression Model
- Adaptive Boosting (AdaBoost)
- Random Forest Regression (RFR)

The results of these papers showed that AdaBoost had the best performance with MAE of 11.17 and 5.35 mmHg for the SBP and DBP respectively.

In this project, I would like to test some modifications and enhancements that may improve the results of BP estimation as follows:

- Advanced Features
  These papers relied on feature extraction based on characteristic points of the PPG signal. The measured PPG signal may suffer from some distortion that causes an error in detecting these points especially the peak and the foot points. Therefore, using the first and second derivatives of the PPG signal can reduce the effect of this distortion and lead to more accurate features through better estimation of these characteristic points as shown in [7].

- PCA
  Principal Component Analysis (PCA) can remove the noise in the features. The effect of applying PCA on the features will be studied by reporting the BP estimation error before and after using PCA.

- Feature Selection
  Adding more features may cause overfitting problem. Therefore, feature selection will be used to limit the number of features used by the regression model. In addition, the importance of the features will be analyzed to determine the most effective features for estimating SBP, DBP, and MAP.

- Data Trend
  The current methods estimate each BP reading independent of the previous readings. However, the BP may have some trends or patterns that help in improving the prediction. For instance, the changes of BP from beat to beat are expected to be small. Therefore, the

prediction algorithm should take into account the BP estimations of previous beats in predicting new reading. Some literature survey is required to understand the known techniques to implement this idea.

PROJECT SCHEDULE:

This project shall be completed during the fall semester till 13th of December within 10 weeks. So, the project can follow some milestones as shown in the following schedule.

Task Description	Duration
Understand the structure of the dataset, remove corrupted samples and determine missing data. Extract the features from the ECG and PPG signals	1 week
Build the following primary set of regression models: Regularized Linear Regression Model, SVM Regression Model and Adaptive Boosting (AdaBoost)	2 weeks
Milestone 1	
Build the following advanced set of regression models: Decision Tree Regression Model and Random Forest Regression (RFR)	1 week
Compare the results with the published papers that used the same dataset.	1 week
Milestone 2	
Extract the advanced features and compare the effect on the BP error	1 week
Use PCA to decrease the noise in the features and do feature selection	1 week
Detect data trends and find a way to control the regression model output to take this trend into account	1 week
Milestone 3	
Preparing the project presentation	1 week
Writing the final report	1 week
Total Duration	**10 weeks**

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