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Smartphone based Blood Pressure Estimation using CART and PPG

Akshaya Moorthi[1]

[1]Department of Computer Sci. & Engg, Thejus Engineering College, Vellarakkad, Thrissur, Kerala, India

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Abstract - *Blood pressure is closely related with cardiovascular diseases so an easy way to monitor the variation in blood pressure help to diagnose and treat at the initial stage and it also reduces the risk. The commonly used method is cuff-based method but major problem of the method is portability. The other method is cuffless method, which uses pulse transmit time to estimate BP(Blood Pressure).This paper proposes Photoplethysmography(PPG) based cuffless method to estimate blood pressure and its an android application using Classification and Regression Tree(CART).Initially the user place the finger tip on the back camera continuously, PPG signals from the frame sequence are extracted and process it by using CART model .The MIMIC II data set is used to extract raw PPG signal and used for training the system. Pulse area, pulse rising time and width are the attributes used to predict systolic and diastolic blood pressure. The model is compared with linear regression, ridge regression, the support vector machine and neural network in terms of accuracy rate, root mean square error, deviation rate and training time and draw the conclusion that the proposed algorithm meet the acceptable accuracy.*

Key Words: **Classification and regression, pruning.**

1. INTRODUCTION

The existing BP measurement method can be divided into two categories, invasive and non-invasive measurements. Invasive measurements are accurate but traumatic and limiting its widespread clinical use as it is less portable and not user friendly. The non-intrusive method are more likely to accepted because it is less intrusive.

Today, smartphones become increasingly popular and equipped with high-end processors and high-resolution cameras. Motivated by these diverse capabilities of smart phones, this project focus on utilizing them for biomedical applications, an alternative way to measure blood pressure by applying smartphone-based photoplethysmogram (PPG) acquisition.

PPG is an optical technique which can be used to estimate blood volume changes of an organ. By the assumption of PPG that skin illumination with penetrating optical radiation can be detected the signal by a photodetector we can use Android smartphone's camera equipped LED flash for recording the intensity of light from the fingertip. blood volume. The acquired frames and their histograms of RGB channels were computed for finding their means and distributions. The method is depicted in the Fig-1.

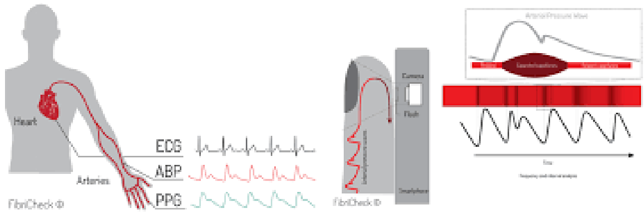

Fig -1: Blood pressure monitoring

1.1 Background

From the Greek word plethysm to increase, plethysmography means "finding variations in the size of a part owing to variations in the amount of blood passing through or contained in the part." Plethysmography refers to the technique for detecting cardiovascular pulse wave traveling through the human body measuring pulsatile tissue volume directly. Arterial pulsations are the most significant reason for volume changes. Capillaries are largely non-compliant and will register only minor pulsations. The plethysmogram is used as an indirect measure for arterial blood pressure (ABP).

With a digital camera in movie mode using ambient light Photoplethysmography signals can be measured remotely or internally. PPG is based on the principle that blood absorbs more light than surrounding tissue so variations in blood volume affect transmission or reflectance correspondingly. In red blood cells, one of the major components is oxygen carrying protein, hemoglobin, pigmented with red color. This characteristic makes the light properties of blood absorption spectra give us a key factor in the application.

The absorption is highest for the green part of the spectrum and it is lowest in the blue part. PPG signals can be divided in two parts: DC component and AC component. The DC component is a constant voltage offset determined by the nature of the material the light passes through. The AC component is a Component synchronous to the heart rate. The AC component of PPG pulse shapes are indicative of vessel compliance and cardiac performance.

In the AC component of PPG signal we can see the changes by fluctuations due to blood flow with the highest amplitude values in the areas with highest absorption. The analysis is based on the statistical signal processing theory and the knowledge about the hemoglobin absorption spectra.

The paper is organized as follows. Section II describes the PPG methods for the BP evaluation. Section III describes the CART and the data set used in the system. Section IV draws some conclusions and ongoing activity.

2. LITERATURE REVIEW

Nowadays most of the blood pressure measuring devices rely on a common concept of inflatable cuff to the arm which is based on auscultatory or oscillometry principle. But this analysis is focused on the cuffless methodologies. In [2] discusses PPG methodology to detect blood pressure using regression and the attributes derived from the shape using MATLAB but the training time is very high. In [3] a method regardless of its shape is proposed. Whole-based, uses raw values of the PPG signal at a given time interval for estimating the BP. In fact, compared to parameter-based methods, our algorithm is independent of the form of the PPG signal. The result is acceptable in terms of accuracy but the size of data needed for training is large.

In order to improve the performance of the system regression model with RReliefF algorithm to select a subset of relevant features is used in [4] but in this the prediction accuracy is highly rely on the amount of data and it need an additional sensor. Focusing on the accuracy artificial neural network (ANN) with multitaper method (MTM) for feature extraction is implemented to obtain the mean absolute error is 4.02 ± 2.79 mmHg for systolic BP and 2.27 ± 1.82 mmHg for diastolic BP and this method has the possibility to further reduce the error using deeper analysis.

In [6] presents a low-cost and a miniaturized pulse oximeter to continuously measure patient's blood-oxygen saturation level (SpO_2) and pulse rate. . As the PPG signal is mostly corrupted by patient's hand movement, it is given to LabView window by DAQ card for further signal processing. In this paper a low pass filter is used for removing motion artifacts and a moving average algorithm is applied to remove high frequency noise content. The SpO_2 is calculated by computing the AC and DC components of both the red and infrared LEDs corresponding PPG signals. The pulse rate is determined by time domain peak detection algorithm in LabView signal processing module. This required additional hardware.

3. METHODOLOGY

In this smartphone is used to evaluate BP without the need of additional hardware. The PPG is extracted by processing each frame acquired by the integrated camera, it examines each geometrical figure defined by brighter pixels and then it is processed by Classification and Regression Tree to evaluate the Systolic BP and Diastolic B.Th. overall system is implemented in Java.

The overall process can be divided into six steps.

1. Initialization phase
2. PPG extraction
3. Frame validation
4. PPG computation
5. Build CART
6. Evaluate PPG using CART

The flow diagram of the picture is depicted Fig-2 .The step 1-4 comes under the image processing and the 5-6 is CART construction and processing, the system used MIMIC II dataset for the prediction.

3.1 Image Processing

In the proposed method, left or right hand fingertips are held on smartphone camera lens with flash for 30 sec with flash. PPG data can be considered of two types - a. Reflective Mode (Video with flash) b.Transmission mode (Video without flash). FPS of mobile camera is also an important parameter for capturing video and experiment has shown its range in between 25-30 FPS and we have used same data as sampling frequency for corresponding video.

The captured image is in RGB format so every pixel consists of R (0-255), G (0-255), B(0-255) values. For Proper touch measurement, we have used a. average intensity count of frame in red channel b. histogram analysis for red, green and blue channel c. Rules and Values for different parameters d. Gray scale image conversion and analysis (binary method). Under histogram analysis, if LED is turned on, then G and B channel intensity values are lower half of the histogram means less than 128.

If more contact pressure is produced on camera:

a. Deforming arterial wall leads to wrong reading

b. Block micro circulation in the capillary

c. Sudden up & down of pixel intensity.

d. After FFT analysis of brightness signal flat line (Y=constant) is produced

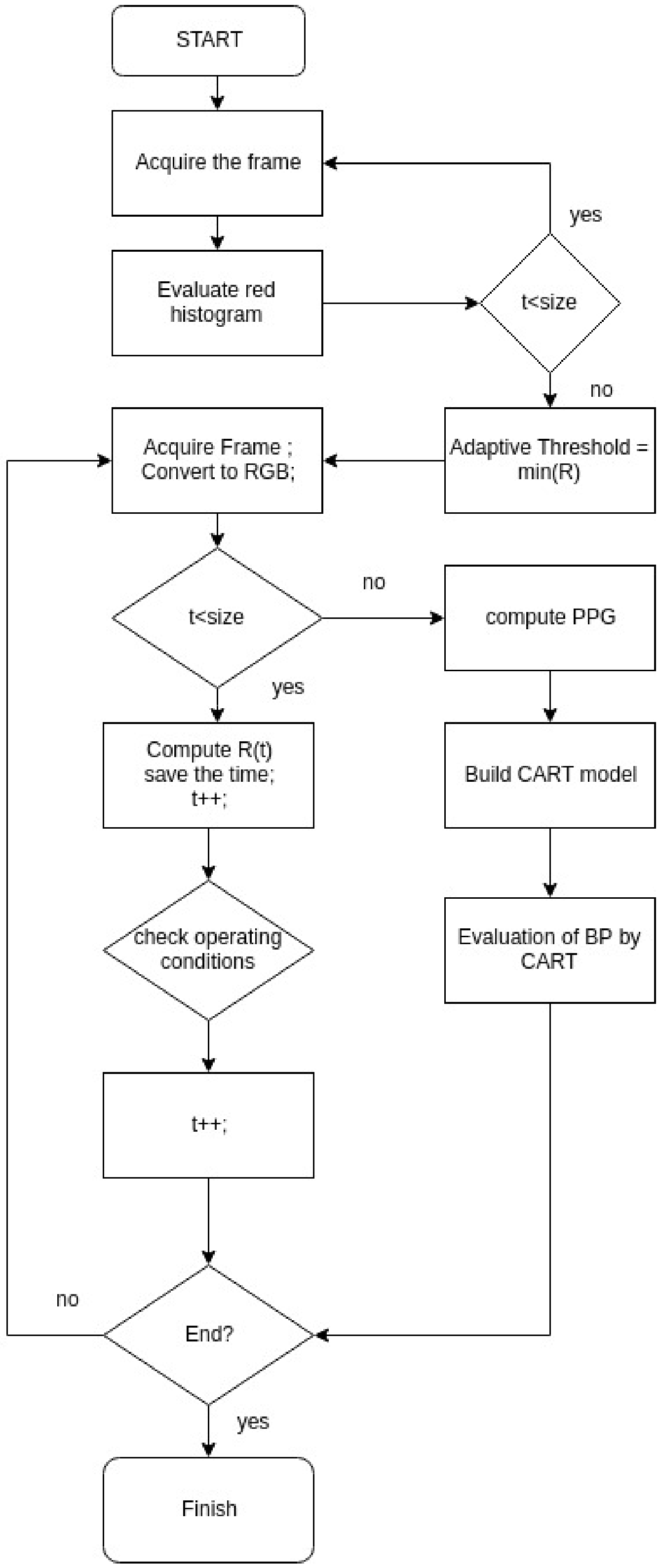

Fig -2: Flow chart of process

3.3 MEAN SQUARE ERROR (MSE)

This is a feature selection method to generate the binary tree. Feature space X is treated as combination of N m-dimensional vector x and m represent input feature.

$$D^{n*m} = \begin{bmatrix} X_{11} & X_{12} & X_{1(m-1)} & y_{1m} \\ X_{21} & X_{22} & X_{2(m-1)} & y_{2m} \\ X_{31} & X_{32} & X_{3(m-1)} & y_{3m} \\ & & & \\ X_{n1} & X_{n2} & X_{n(m-1)} & y_{nm} \end{bmatrix}$$

The $X_{ij}$is the jth attribute of the ith data sample.$X_{i1}$is the set of attributes and the sorted can be represented as $a_1, a_2 \ldots\ldots a_n$.The partition value $T - i1$ can be represented as :

$$T_{i1} = \frac{a_i + a_{i+1}}{2}$$

and the MSE(T_{ij}) can be calculated as :

$$MSE(T_{ij}) = [min(c1) \sum_{x_i \epsilon D_i} (y_j - c_1)^2 +$$

$$min(c2) \sum_{x_i \epsilon D_{i+1}} (y_j - c_2)^2]$$

This process will continue until the D_i and D_{i+1}reach a steady state.Fig-3 represents the first division.

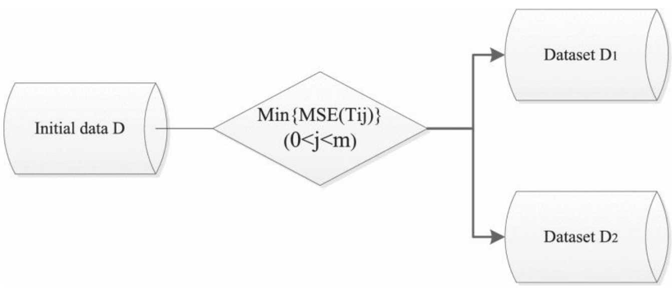

Fig -3: First division of CART

3.2 CART Model

The CART (classification and regression tree) model proposed by Breiman [11] in 1984 has become a widely used decision tree learning method. The CART method assumes that the decision tree is a binary tree. The input feature space is divided into finite units, based on which the predicted values are determined, i.e. the predicted output values are mapped to the given conditions. The CART model is composed of the following three main steps:

(1) CART initialization: generating a decision tree based on training data set;

(2) CART pruning and optimization.

The regression tree is pruned according to some constraints, such as the maximum depth of the tree, the minimum sample number of the leaf node and the node's minimum impurity; and the model has best generalization through the combination of different parameters (the maximum depth of the tree (max_depth), the minimum sample number of leaf nodes (min_samples_leaf), the minimum impurity of the nodes (min_impurity_split)), for each combination of different parameters generated different CART models.

(3) CART prediction: put the test set into the trained model and predict it. Compared with other classical classification and regression models.

The first stage of CART division is shown in Figure 3.6 .

CART has the following advantages:

1) Less data preparation: no data normalization is required;

2) The ability to handle continuous and discrete data simultaneously;

3) Capable of handling multiple classification problems;

4) The prediction process can be easily explained using

Boolean logic as opposed to other learning models such as neural network and SVM

Algorithm: DecisionTreeRegressor

Input:D = ((X1,Y1),(X2,Y2),(X3,Y3)..(Xn,Yn))where X = (X1,X2,X3..Xn) represent the feature property set , Y = (Y1,Y2,Y3.... Yn) predicted attributes.

1.for □ ∈ $(1, Q)$

2. for □ ∈ $(1, Q)$

3. for ∈ $(1,Q)$

4. for x_i in X

5. for T_j in x_i

6. search min(MSE)

7. end for

8. end for

9. Build Trees TreeModel from T_j and x_o

10. if H(D) <= $\boldsymbol{\gamma}$ && current depth < □ && |D|>=□

11. Divide D to D_1 *and* D_2

12. DecisionTreeRegressor(D_1□,□,$\boldsymbol{\gamma}$);

13. DecisionTreeRegressor(D_2□,□,$\boldsymbol{\gamma}$);

14. else if(|D|<□)

15 drop D

16. else

17. D →leaf_node;

18. predictive value = avg(D)

19. break;

20 end if

21. end for

22. end for

23. end for

The Algorithm [1] , 1 to 3 traverse all the feature parameter combinations, and each parameter combination is modeled subsequently. Line 4 to 9 mean the least square error minimization criterion used to obtain the feature attributes and partition points of the split selection. When the feature selection is started, build a tree step by step. Line 10 to 11 describe the pruning process of the tree according to three indicators (γ , α, β), once the condition satisfied, the dataset D would be split into two sub trees D 1 and D 2 , which is expressed in line 12 to 13. Line 14 to 15 suggest that if the sample number of the nodes is less than β, the node would be dropped. Line 16 to 19 shows that if the node does not satisfy all these conditions, it will convert itself to a leaf node whose output value is the average of the samples on the node. Finally, the process of BP prediction is conducted by using the obtained TreeModel in Line 24.

4. CONCLUSIONS

CART algorithm is robust to the noisy data and able to make a better-fitted algorithm for discrete target data . Researchers used the CART for PTT-based cuffless BP The reason behind the success is their non vulnerability to the outliers.

Most importantly, this study further analysed the estimation accuracy of the machine learning algorithms under different BP categories (normotensive, hypertensive, and hypotensive) and found that most of the algorithms exhibited better accuracy in the normotensive category. Previous research only presented overall BP accuracies (overall mean of difference ± SD of difference) rather than individual categorical BP accuracies [3,9,36]. Some studies only included normotensive subjects [10,17,37]. In our study, CART was found with higher mean BP difference and SD of difference in hypertensive and hypotensive categories in comparison with the normotensive group. This could be caused by the low amount of data within the hypertensive and hypotensive categories of the online database. To make an accurate algorithm for each BP category, it is therefore suggested that the specific algorithm approach for different BP categories should be considered in a future study.

This study has some limitations. Firstly, the checking to determine the quality of PPG signal segments is not practical in real scenario. The development of advanced preprocessing algorithms to automatically determine signal quality is important. It is also worth investigating the effect of noise on the estimation accuracy of machine learning models. Secondly, the training and test of the three machine learning algorithms were limited to the database of the MIMIC II. It would be useful to test the algorithms in a new database. Thirdly, due to the lack of the basic clinical variables (e.g., BMI, gender, weight, and height) in the dataset, these variables were not included to train the machine learning algorithms, which may improve the measurement accuracy of some of the algorithms . Finally, the BP estimation was performed on the basis of each segment and only noninvasive intermittent BPs were available to be used as reference BPs to train the algorithms. In a future study, using continuous BP as reference BPs may improve the algorithms, allowing beat-to-beat BP estimation

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