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# A Unique Framework for Contactless Estimation of Body Vital Signs using Facial Recognition

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***Abstract- As one of the consequences of COVID-19 pandemic, a lot of new technologies are developing in fast-track pace in clinical practices. The main idea of our project is to design contactless technology for the support of patients who suffer from blood pressure disorders and coronary heart diseases using machine learning approach. This may intend people to monitor their heart rate, pulse rate, respiratory life and oxygen saturation levels at an ease. The orientation of this paper is to monitor the blood pressure considering the facial changes and movements in a video to get rid of cuff-based measurement of blood pressure. We analyzed whether blood pressure can be obtained in a contactless way utilizing a novel technologies like image processing and machine learning techniques. This innovation estimates vague facial blood stream changes from video recordings captured by camera with the help of machine learning and image processing techniques.***

***Keywords*: *Signal Processing, Machine Learning, Principal Component Analysis, Image Processing, hypertension.***

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## I. INTRODUCTION

Estimating blood pressure (BP) is a significant perspective in observing the health of a patient. Hypertension implies that a patient has a high risk of medical conditions. Hypertension puts of strain on the arteries and the heart. This strain can make the veins less adaptable over the long run. As they become more resolute, the lumen becomes smaller. In this way, its likelihood of being clogged up increases. Coagulation is perilous and may cause heart attack, stroke or kidney problems. Thus, it is significant for an individual to screen their blood pressure frequently which doesn't require a doctor's supervision. In this initial study on normotensive subjects, we show that this technology exhibits comparable accuracy to traditional automated blood pressure monitors. However, transdermal optical imaging technology implemented on a smartphone would improve upon traditional cuff-based devices by being more convenient and more comfortable (e.g., cuff-less) [7]. This is likely to encourage measurements in more places and with more regularity than before and provides a comprehensive picture of patients' blood pressure throughout the day, much like an ambulatory blood pressure monitor. The commonly measured body vital signs are usually determined through the traditional contact based instruments or through wearable biomedical instruments. Heart rate variation can be determined by the vigorous non- contact methods [1]. Blood pressure estimation is the important parameter for the prior understanding of a cardiovascular disorder as it is interrelated with the indication of hypertension or hypotension. In case of any abnormal variation in the BP would indicate the risk in cardio vascular disorder.

The primary method for measurement of BP is by using a sphygmomanometer which contains a cuff. The cuff provides a discomfort to the patient for continuous measurement of BP. In this study, we considered other body vitals along with blood pressure and heart rate in terms of six body vital signs as illustrated in the table 1.1. The vital signs vary in person to person and they differ by age, sex, and medical condition [25]. The research work and frameworks focuses on examining the six body vital signs as the main goal. As mentioned y the previous studies, the ECG and PPG signals helps in measuring the BP and heart rate estimation. Muhammad Kauchee *et al* [16] and Hendrana Tjahjadi *et al* [4] detailed about the blood flow in the arteries. The studies relied on discussing about the measurement of BP through PPG signals. The related background work summarizes about the traditional methods and frameworks associated to measure heart rate and BP based on PPG signals.

 

The traditional methods for the estimation of BP involves with cuff as well as cuffless techniques. The BP estimation based on PPG using a cuff involves a small cuff around the finger which contains a built-in sensor. This approach provides a discomfort during continuous monitoring. This basic approach has been overcome by BP estimation without cuff using PPG. The measurement of BP without cuff using PPG includes three main methods- Pulse Transit Time (PTT), Pulse Wave Velocity (PWV) and Pulse Wave Analysis (PWA) methods. The PWV can be easily determined by using transit time and transit distance but finding an arterial location requires a medical expert supervision [16], [2]. There are two ways for achieving BP estimation that is parametric and non-parametric models [4][16]. The remote Photoplethysmography (rPPG) technology is a non-contact physiological parameter detection technology based on PPG [6]. The measured location and the intensity variation are recorded with video and the pulse wave signals can be extracted from the blood volume variation. Through the analysis of the feature vectors of the pulse wave signal, the heart rate, respiratory rate and oxygen saturation such physiological signals can thus be obtained [11].

There are so many established regression methods, such as support vector machines (SVM), linear regression, regression trees, model trees, ensemble of trees, and random forest. The regression models for BP estimation involve the unknown parameters of the model denoted as α (algorithm-specific), the independent variables X (features from PPG or ECG) and the dependent variable Y (either SBP or DBP). In [16], the authors proposed the GA-SVR (Genetic Algorithm Support Vector Regression) BP models to estimate the SBP and DBP. In the research performed in the authors estimated the SBP and DBP values using a Regression Tree, Multiple linear regression (MLR), and SVM. A 10-fold cross-validation was applied to obtain overall BP estimation accuracy separately for all three machine learning algorithms.

Most studies determine the chances for evaluation of blood oxygen saturation levels in a contactless approach with help of variations in the wavelengths ranges of two video images. It has been also observed in most studies that a variation in the green component of the captured video images of the face results as a pulse signal. A very few studies reported the estimation of the blood pressure estimation [20].

Table 1: The Normal range of values for different vital signals

| ***Bio Signal*** | ***Acronym*** | ***Normal range*** | ***Vital Signal*** |
|---|---|---|---|
| Heart Rate | HR | 60-100 beats per min | HR |
| Systolic Blood Pressure | SBP | 90-120 mmHg | BP |
| Diastolic Blood Pressure | DBP | 60-90 mmHg | BP |
| Mean Blood Pressure | MBP | 60-100 mmHg | BP |
| Respiratory rate | RR | 12-18 breath per min | RR |
| Blood Oxygen Saturation | SPO2 | 95-100% | SPO2 |

This paper focuses on the medical condition of the patients who suffer with the heart problems. In this regard, this novel framework aimed to calculate blood pressure along with other body vital signals such as heart rate, respiration rate and oxygen saturation levels. This paper is written with the motivation from all the research studies which helped in presenting an efficient contactless technique for the extraction of blood pressure and other body vital signs. Moreover, the PPG and ECG along with ABP are used to calculate the Systolic and Diastolic Blood Pressure along with HR using the face video. The accuracies obtained for the estimations for this proposed technique depicts that it is safer to examine as a continuous and contactless cardio screening device.

The remaining paper is organised as follows: Section II explains the proposed methodology for the extraction of blood pressure along with other body vital signs with the captured ppg signals. Section III summarizes the experimental setup and the results of the framework which is followed by Section IV. The section IV gives the details about the discussions future scope and advantages of the proposed methodology.

 

## II. PROPOSED METHODOLOGY

In this paper, we explore an approach to propose a novel method for classifying BP, heart rate, respiratory rate and SPO2 signs using image processing and machine learning techniques. We also intend to use signal processing technique to extract and amplify cyclical blood pulsations within the human facial vasculature [7]. The detailed block diagram of our methodology is illustrated in the figure.

### *A. Database*

In this paper, the database is a processed version of the Multi-parameter Intelligent Monitoring in Intensive Care (MIMIC) II online waveform database provided by PhysioNet organization is used as a source of ECG and PPG signals [5].This sample data consists of Systole, Diastole Blood Pressures and MAP (mean arterial pressure). MAP is defined as the average pressure in a patient's arteries during one cardiac cycle. It is considered a better indicator of perfusion to vital organs than systolic blood pressure (SBP). True MAP can only be determined by invasive monitoring and complex calculations; however it can also be calculated using a formula of the SBP and the diastolic blood pressure (DBP) [16].

$$MAP = \frac{SBP + 2\,(DBP)}{3}$$

The collected database consists of 5599 record parts having all of the ECG, PPG, and ABP signals. However, after removing the record parts with insufficient record durations (less than 10 min) or with very high or very low BP values (e.g., SBP $\geq$ 180, DBP $\geq$ 130, SBP $\leq$ 80, DBP $\leq$ 60), the final database consists of 3663 record parts associated with about a thousand unique subjects [16]. Each part has its own unique ID, which indicates its record and part numbers. ID field is used in the training and test process to prevent overlapping the subjects of the training set with that of in the test set. Fig. 2 and Table I demonstrate some statistical information about the distribution and ranges of the DBP, MAP, SBP, and HR values in the final database. Each instance is also given a unique ID to prevent overlapping of the data in the dataset. The dataset is then split into 80% for training and 20% testing. Thereafter, the signals are pre-processed before it is used to build a machine-learning model [5].

### *B. Image Processing*

Detection of body vital signs through image processing involves detection of facial color signals. This image processing phase involves two main phases. Firstly, the facial region must be detected in each frame of the video since the face is the only portion of the frame that will contain heart rate information. Second, the desired region of interest (ROI) within the face bounding box must be chosen.

***Face Detection and Tracking*** Voila and Jones [26] proposed a Haar Cascade classifier for the detection of the face. We intend to use the OpenCV cascade classifiers pre trained on positive and negative frontal face images. The face detector is built from a cascade of classifiers of increasing complexity, where each classifier uses one or more Haar-like features. To achieve invariance with respect to lighting and scale, sub-windows are normalized and the final detector is slid over the image at varying window sizes. Any overlapping positive-classification windows are averaged to create a single facial bounding box. This face detection algorithm is applied to each frame in the video and outputs a bounding box for each face it detects. To maintain consistency across frames, if no face is detected in a frame, the face from the previous frame is used, and if multiple faces are detected, the face nearest to that in the previous frame is used [8].

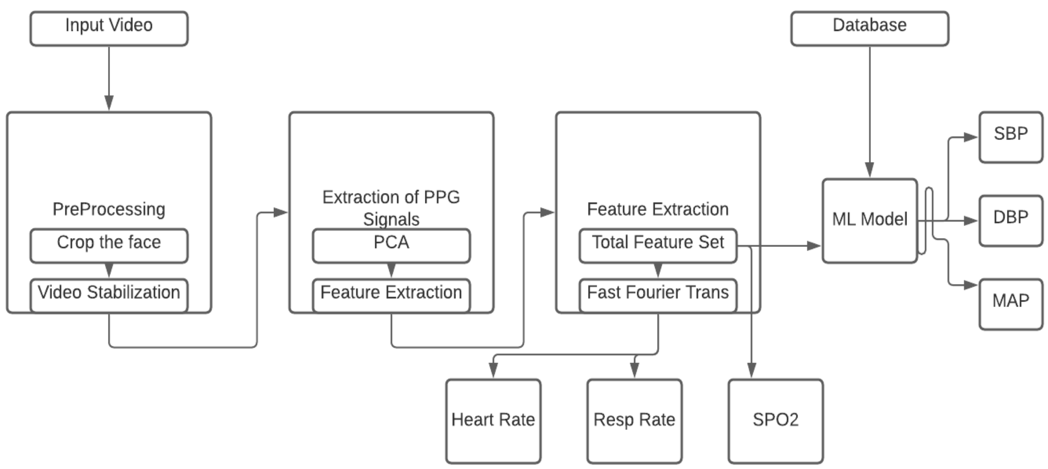


Fig 1: Proposed Block Diagram

***Region of Interest*** The face bounding box is detected using the face detection method which has background pixels in addition to facial pixels. An ROI is to be selected from the constituted bounding face box. Poh et al [8] had done a method for selecting the ROI where the centred 60% width of the bounding box and full height was extracted. This method simply removes the background pixels that are left to te sides of the face. From the obtained face box, it is intended to remove the eye portion as the eye portion contains the non-skin pixels. The eye movement and blinking results in varying the pixels from frame to frame which disturbs the efficiency of the signal extraction. The paper also focuses on working to retain only the pixels above the eye region since Verkyusee et al. [8]has found that forehead has the strongest plethysmographic signal.

### *C. Principal Component Analysis*

PCA is the technique used for dimensionality reduction of multivariate dataset. The multivariate dataset is the aligned collection of PPG signal of single period cycle. The algorithm can be applied to aligned PPG signal. [14]. Once we have an ROI for each frame, we read color the color signals from the forehead region. We take the average of the pixels in the ROI across each color channel to get the three signals $x_R(t)$, $x_B(t)$ and $x_G(t)$ at time t. PCA has found a widespread application in ECG signal processing. We use the PCA to derive the data using Eigen vector into principal components where this method is known as Eigen decomposition [14]. PCA helps in normalizing the color signals to the subjective source signals that helps in extracting the required vital sign features [12].

### *D. Extraction of Heart Rate and Respiration Rate and SPO2 levels*

Once we have the source signals, we can apply a Fourier transform to the data to examine their power spectrum and determine the prominent signal frequencies [22]. We can isolate frequency peaks in the power spectrum within the range 0.75 to 4 Hz, which corresponds to physiological heart rate ranges of 45 to 240 bpm. The measured heart rate will be the frequency within the acceptable range corresponding to the peak with the highest magnitude. Similarly, the measured respiratory rate range is evaluated considering the normal range of the respiration rate [23]. The SPO2 is obtained as the percentage through the face box itself.

### *E. Blood Pressure Measurement Model*

The Performance of Blood Pressure Estimation tested under many regression models [7] [5].To predict the BP, we use the basic regression framework, y = Px where y represents the vector of expected BP (systolic or diastolic), P is the matrix of parameter vectors – the rows of P correspond to different individuals and the columns correspond to the various parameters (which is equal to 21 here, as shown in Table I), and x is the regression weights (to be estimated). The regression framework is simple to interpret; the regression weights tell us the relative importance of various parameters in BP prediction.

**Regression Models** Once the features are extracted, the following are the various machine learning models considered to find the possible association between input features and the blood pressure [5]. The feature vectors are trained using all the models and compared with each other. Also, separate models are trained for estimating the targets such as SBP, DBP and MBP.

**Linear Regression** is a simple regression used for predictive modelling and easy to implement as well. It gives an equation with slope and intercept that predicts the target values. The relation between BP, denoted as Y and input features as $x_1$, $x_2$,. . .$x_n$ are expressed in the equation

Y = ˛o + ˛1x1 + ˛2x2 + . . ...˛nxn

where ˛1,˛2,. . ..˛n are coefficients obtained from the model [16].

**Decision Tree Regression:** This regression trees build models in the form of a tree structure, which consists of a number of decision nodes that each selects a branch based on a trained condition [5]. An input traverses decision nodes of a tree to a leaf node which determines the final prediction value. Decision trees are models which are easy to understand and interpret. However, in some problems, they can create over-complex structures that do not generalize well, and hence demonstrate a poor performance.

**Support Vector regression:** Unlike simple linear regression, this helps to minimize the errors within the boundary line by separating the dataset using the hyper plane. The kernel function is used to transform the data into higher dimension to perform the linear separation [16]. Support vector regression uses support vector machine, which constructs the hyper plane between the data points which is the best fit line that has maximum number of points. Radial basis function is used as a kernel and Sci-kit library is used to train the regression model.

**Adaboost regression:** It is the boosting algorithm, i.e., it can be combined with any other machine learning algorithms to improve the performance. It combines all the weak learners to predict the target value. Predictions are made by calculating the weighted average of the weak classifiers. Here, 1000 number of decision trees are used to train a model. It is also less susceptible to the overfitting problems.

**Random forest regression:** This Regression is one of the most effective models of machine learning for predictive analysis. It is good at estimating the output even when the features are in non-linear relation with targets[15]. RF also reduces the overfitting, i.e., it reduces the variance bias trade off by combining the predictions of every decision tree. Diversity in every tree results in the robustness of the model. Sci-kit library is used to train the regression model.

**Feature selection:** Among various machine learning algorithms, the best model that provides least error is Random Forest that obtains the optimal feature set separately for SBP, DBP and MBP. Random forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model. The inverse of mean absolute error from the ML model is considered as the fitness function.

In this comparison, simple regression models (i.e., linear regression and decision tree), strong and nonlinear models (i.e., RBF kernel SVM) as well as boosting and ensemble methods are included. The performance of the BP estimation using linear regression is much lower than the estimation performance when using strong nonlinear learning algorithms such as kernel machines or ensemble learning methods. Especially, in the whole-based approach, linear regression and decision tree are almost incapable of producing acceptable accuracies. On the other hand, other models such as SVM, AdaBoost, and random forest are more promising [16]. Considering the mean absolute error (MAE) criterion, the Random Forest approach outperforms the others by a margin. The model weights were inspected using the Gini importance, which measures the importance of each feature in terms of the total reduction of the tree splitting criterion. It turned out that, compared to other features; PATd feature is playing a more significant role in the BP prediction.

## III. RESULTS

Our study tested the hypothesis that this proposed framework accurately detects the body vital signs from the video of the face. First, we determined the Oxygen saturation levels with the help of wavelength propagation from the face box. Second, the heart rate and respiratory rate are assessed against the reference data. Later, we quantitatively assessed our BP prediction model against the reference systolic, diastolic measurements.

The results clearly indicated that the extracted respiratory signal is having a strong correlation with that of the actual respiratory signal. The table II illustrates the results of the accuracy rate calculated from the original Respiratory rate and the extracted Respiratory rate.

Table 2. Accuracy calculations for Respiratory rate.

| ***S. No*** | ***Original RR*** | ***Extracted RR*** | ***Accuracy (%)*** |
|---|---|---|---|
| 1. | 10.38 | 10.36 | 99.92% |
| 2. | 12.57 | 12.57 | 100.% |
| 3. | 15.76 | 15.56 | 97.57% |
| 4. | 14.15 | 14.14 | 99.94% |

BP measurement was estimated using many regression models like Linear Regression, AdaBoost, and Random Forest. Based on the accuracy level, we considered Random Forest for this paper which gave us nearly 80% accuracy. Even the error rate is least for Random forest. The accuracy for Systole and Diastole is 0.84 and 0.79 respectively with random forest. The following Table 2 shows the comparison of MAE and RMSE on various ML algorithms. Different combinations of features are investigated to demonstrate the improvement in performance due to the proposed features on various ML algorithms.

Table 3: Comparison of performance of various ML methods using different feature set

| BP | Feature set | Machine Learning Techniques | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Linear Regression | | Ridge Regression | | Support Vector Regression | | Adaboost Regression | | Random Forest Regression | |
| | | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE | MAE | RMSE |
| **SBP** | ALL | 14.05 | 17.78 | 14.23 | 18.04 | 14.85 | 18.92 | 14.20 | 17.17 | 10.83 | 14.96 |
| | PTT + PPG features | 15.27 | 18.90 | 15.19 | 18.94 | 15.14 | 19.30 | 15.63 | 19.17 | 14.14 | 18.18 |
| | Physiological features | 15.13 | 18.84 | 15.10 | 18.90 | 14.70 | 19.04 | 16.90 | 20.07 | 11.89 | 15.88 |
| | PTT + ECG features + alpha | 15.06 | 18.91 | 15.08 | 18.81 | 14.94 | 19.07 | 16.18 | 19.44 | 11.16 | 15.00 |
| **DBP** | ALL | 10.76 | 13.92 | 10.94 | 13.92 | 10.98 | 14.41 | 11.99 | 14.32 | 8.43 | 11.62 |
| | PTT + PPG features | 11.37 | 14.38 | 11.41 | 14.31 | 11.17 | 14.61 | 12.52 | 14.98 | 10.58 | 13.73 |
| | Physiological features | 11.06 | 14.05 | 11.40 | 14.30 | 11.08 | 14.51 | 11.81 | 14.36 | 9.38 | 12.54 |
| | PTT + ECG features + alpha | 11.35 | 14.33 | 11.21 | 14.12 | 11.05 | 14.47 | 12.11 | 14.45 | 8.55 | 11.84 |
| **MBP** | ALL | 10.44 | 13.28 | 10.59 | 13.30 | 10.70 | 13.76 | 10.95 | 13.07 | 8.35 | 11.05 |
| | PTT + PPG features | 11.19 | 13.86 | 11.14 | 13.77 | 10.95 | 14.01 | 12.06 | 14.36 | 10.22 | 13.12 |
| | Physiological features | 10.86 | 13.58 | 11.09 | 13.76 | 10.77 | 13.95 | 11.27 | 13.55 | 9.11 | 11.91 |
| | PTT + ECG features + alpha | 11.08 | 13.79 | 10.95 | 13.60 | 10.75 | 13.83 | 11.96 | 14.10 | 8.45 | 11.33 |

Similarly we intended to calculate the Heart Rate and Oxygen Saturation Levels with better accuracy. The below figure summarizes the obtained body vital signs.


## IV. CONCLUSION

This paper proposes a novel approach that extracts the PPG using face video and estimates the BP and HR based on it.The proposed methodology consists of signal de-noising, feature extraction, and regression stages. The time-domain features are extracted from the ECG and PPG signals for the continuous cuffless blood pressure estimation. Experiments have been performed to testify the feasibility of the proposed non- invasive BP measurement method. During the practical tests, the light intensity, facial motion and the distance between the face and the camera would have effect on the measurement result. The participant should kept his/her face as still as possible and the optimal distance between the face and the camera is around 60 cm under normal daylight circumstances, which would be easy to set such measurement environment. Factors like skin complexion have been overlooked in this study; it is challenging to extract PPG from the face video with a darker skin-tone.

## V. FUTURE WORK

This approach is tested over an online database that mostly had young and healthy volunteers. Since, BP estimation using the video based PPG has been explored; there is only one suitable online database on which the experiments can be conducted [3]. In future, we look forward to collect and work with bigger and diverse databases, collected at government dispensary. This database will include old and young subjects with known cardiovascular diseases and a variety of skin-tone. Our future work will be based on improving the robustness and accuracy of the proposed approach [3].

This approach can be easily modified into a mobile application and software, which can be used with android mobiles and laptop/computers. In future, the proposed approach can be used for stress management and hypertension monitoring at home, office, school, college, meditation and medical centres. It is an inexpensive, compact and time efficient approach that can be readily used whilst involved in your day to day activities.

Future work will investigate how to tune the parameters in the BP model to adapt in more general scenarios considering different applicable requirement. Besides, the online adjusting scheme would be explored to design the model to setup the baseline of the tester for long-term personal health monitoring.

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