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Monitoring Blood Pressure Using Regression Techniques

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***Abstract*—**Blood pressure helps the physicians greatly to have a deep insight into the cardiovascular system. The determination of individual blood pressure is a standard clinical procedure considered for cardiovascular system problems. The conventional techniques to measure blood pressure (e.g. cuff method) allows a limited number of readings for a certain period (e.g. every 5-10 minutes). Additionally, these systems cause turbulence to blood flow; impeding continuous blood pressure monitoring, especially in emergency cases or critically ill persons. In this paper, the most important statistical features in the photoplethysmogram (PPG) signals were extracted to estimate the blood pressure noninvasively. PPG signals from more than 40 subjects were measured and analyzed and 12 features were extracted. The features were fed to principal component analysis (PCA) to find the most important independent features that have the highest correlation with blood pressure. The results show that the stiffness index means and standard deviation for the beat-to-beat heart rate were the most important features. A model representing both features for Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) was obtained using a statistical regression technique. Surface fitting is used to best fit the series of data and the results show that the error value in estimating the SBP is 4.95% and in estimating the DBP is 3.99%.

***Keywords*—**Blood pressure, noninvasive optical system, PCA, continuous monitoring

I. Introduction

BLOOD pressure (BP) is one of the vital signs for diagnosing cardiovascular diseases and health monitoring. As the BP reflects the physical conditions of the body, it is considered as an important measurement for any clinical procedure and medical examination. In developing countries, cardiovascular diseases are one of the main causes of death (e.g. coronary disease, heart attack, cardiomyopathy, etc.). In Jordan, more than one-third of deaths are related to cardiovascular diseases [1]. These diseases are tied closely to BP variation (hypertension or hypotension).

BP measurements can be carried out using two techniques; direct and indirect techniques. In the direct technique, the measurand is directly accessible, implemented using an intra-arterial catheter [2]. In the indirect technique, a cuff with a sphygmomanometer [3] can be used either manually or automated using an oscillometric device. Another indirect technique is based on impedance plethysmography [4]. The cuff-based BP measurement method (i.e. sphygmomanometer), which has been widely used, is based on auscultation to heartbeats [5]. Although the conventional techniques are simple and painless, some of them are a source of discomfort, do not provide a continuous measurement and causes turbulence to the bloodstream, which affects the accuracy of the measurements and make it ill-suited for monitoring purposes. On the other hand, invasive methods (such as the intra-arterial catheter) are used in hospitals (i.e. in the intensive care units which need complex operation procedures) [2].

A few cuff-less approaches and methods have been presented and demonstrated in the literature for providing continuous BP measurements. One method is based on using a pulse sensor with an impedance plethysmograph (IPG) for the detection of blood volume [4]. However, the complexity of this method makes it less practical for being used in BP monitoring applications. Other techniques based on image sensor and image processing are used to measure BP [6]. Ultrasound technology has been used to measure BP [7]. In this technique, the deformation of the arterial walls causes a Doppler shift in the reflected sound wave indicating systolic pressure point. Another method to measure BP is based on tonometry; where the pulsations generated due to partial compression applied on the artery at wrist can be related to arterial pressure [8]. In this method, an array of sensors is positioned along the wrist to detect artery deformation.

Recently, a number of other concepts have been reported to indirectly estimate the BP signal using other physiological parameters or biosignals [9]. These methods are based on the determination of the pulse transit time (PTT) between two different physiological signals or the same physiological signal recorded at different positions on the body. The relation between BP (SBP and PTT) was found to be inversely proportional and was first reported by Thomas in 1955 [9]. The PTT technique is based on measuring the electrocardiogram (ECG) signal and a PPG signal (called ECG-PPG principle) [10]; where a PPG signal is used to determine the arrival of a pulse wave in the artery. The PTT is calculated from the ECG R-wave to the foot of the PPG pulse. The PTT was also studied based on measuring the PPG signal at two different arterial sites (called PPG-PPG principle) [11]. The time delay between the measured PPG signals was used to calculate both SBP and DBP. The results obtained using the PTT technique between two PPG signals show a good correlation with SBP but weak correlation in DBP.

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Up-to-date, PTT is a very promising approach by means of studies made and results obtained [12]. Most of the studies show that the PTT method was safe, noninvasive and provides continuous monitoring of BP measurements. However, the system complexity and the potential for using this approach as a practical system in clinics need more investigation. Different methodologies were addressed to estimate and monitor the BP noninvasively. In this paper, the PPG signal has been considered to estimate the BP targeting BP monitoring. The PPG signals were analyzed, and the signal's features were investigated to correlate them with BP. In such a system, the advantages of the noninvasive technique can be accomplished (e.g. comfortability and the fast response).

II. System Design

A. PPG Signal

The PPG signal is an optically generated signal that reflects the blood volume changes in the arteries. In this technique, the skin tissue is illuminated with light which is emitted by a source usually with wavelengths in the visible or near-infrared ranges. The light passes through the tissue, interacts with the tissue constituents leading to absorption and/or reflection. Since most of the tissue maintained relatively constant, only the blood volume in the arteries and/or arterioles are variable. Accordingly, the amount of optical density (i.e. absorption) is changed relative to the blood volume-changes. A photodetector (photodiode, phototransistor, etc.) is used to measure these changes converting the amount of the detected light to an electrical signal (i.e. PPG signal) [13].

PPG signals are a popular technique to estimate cardiovascular functions [14] cardiovascular diseases, oxygen saturation (pulse oximetry, heart rate (cardiac cycle), respiration and depth of anesthesia). It has been reported that there is a close correlation between the PPG signal and BP signal, making it very suitable in obtaining BP noninvasively and cuff-less [15].

B. Hardware

The system is composed of two parts; the transmitter part, which transmits optical light intensity through the tissue, and the receiver part, which acquires the light intensity and converts it to electrical signals. The transmitter part of the PPG system is shown in Fig. 1. The driving circuit controls the LED operation with a wavelength of 880 nm to illuminate the fingertip. A 555 timer generates a square-wave signal with a frequency of 1 kHz. Then, using flip-flop, the generated square-wave signal is divided by two. The output of this stage is a square wave signal with a frequency of 500 Hz and 50% duty cycle. The signal obtained is connected with the LEDs via H-bridge, which provides the LED with sufficient current required for optimal operation.

At the receiver side (see Fig. 2), the system consists of a photodiode (PD) with the highest responsivity at 880 nm. The PD is followed by a trans-impedance amplifier as a current-to-voltage converter. The detected PPG signal is processed and denoised using a band-pass filter with corner frequencies (0.05 Hz-35 Hz). A post-amplification stage with a variable gain amplifier is added to optimize the signal acquired from a different subject. In the next section, signal processing of the PPG signals will be addressed which include the features extraction process to correlate the most important features with BP. Several detection algorithms and several ways of segmenting PPG signals are proposed and developed over time [16]. The need for new techniques is controlled by the detection accuracy and the percentage error.

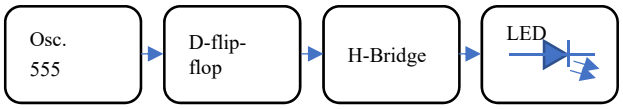

Fig. 1 Block diagram for the transmitter part: deriving circuit for LED

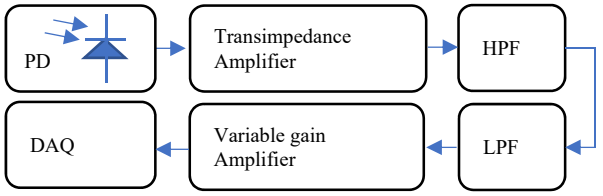

Fig. 2 Block diagram for the receiver part of the system

III. Experimental Procedure

A. Peak Detection Algorithm

The peak detection algorithm (PDA) has been used in PPG signals' segmentation for extracting the main features. As shown in Fig. 3, the PDA algorithm starts with the filtration of the PPG signal to get rid of the noise that was not filtered by the hardware. The filtration process was best made using a moving average filter which smooth the signal to a great extent. The window size had a half-width of five samples. A bandpass filter with corner frequencies (0.1-30 Hz) was also used to restore the baseline and to removing wandering in the signals. Next was the normalization process, where the amplitude of the signal is shifted to the range between 0 and 1. This step is essential to compare signals with a certain threshold and to find the systolic and diastolic peaks (using MATLAB environment). The diastolic peaks (or valley) were found using the same procedure applied to the inverted signals. The last peak in the signal (called notch) was determined using the first derivative of the PPG signals. Then, the index of the peak in the decreasing slope was located and applied to the original signal. The amplitude at that index is called the notch peak.

B. Feature Extractions

Most of the features of the PPG signal are very related to the peaks being detected previously and shown in Fig. 4. Therefore, a robust algorithm must be utilized to perform an accurate estimation. Fig. 4 is a sample of a measured signal using our system. The signal's segmentation process was performed at each diastolic peak followed by the feature extraction step. The main PPG features that were identified using the procedure above are (1) signal amplitude, (2)

systolic area, (3) diastolic area, (4) inflection point area (IPA): it is the ratio between the systolic area to the diastolic area, (5) systolic time, (6) diastolic time, (7) pulse interval, (8) peak-to-peak interval (PPI), (9) heart rate (HR), (10) time at full wave half maximum, (11) augmentation index (AI): it is the ratio between the systolic amplitude to the diastolic amplitude (12) stiffness index (SI): it is the ratio between the systolic amplitude to the time between the systolic point and the dicrotic notch point. Since the PPG signal had been segmented, every PPG sample has many PPG segmented waves. The acquired features had been extracted from each segment. Then, the average and standard deviation of the features had been calculated.

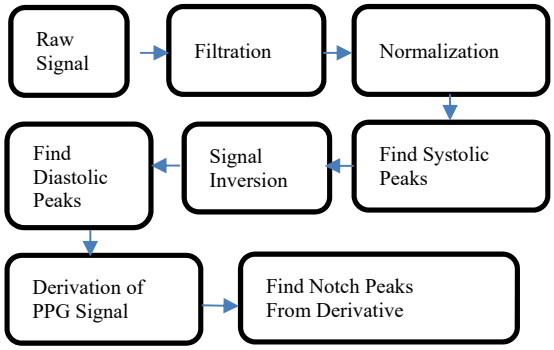

Fig. 3 Block diagram of PDA

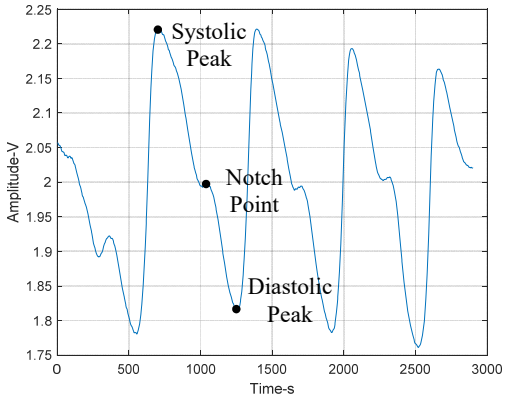

Fig. 4 Example of measured PPG signals

IV. Results and Discussion

The signals had been collected from heart clinic patients with various BP at King Abdullah Hospital, Jordan. The patients were selected based on a predesigned protocol with different elements such as age, height, width, body mass index, gender, etc. Table I shows the subject's demographic data. The signals of all subjects were classified into normal, low and high BP. The signals' features of each class were studied independently for each subject. The features' variation as BP changed was tracked and separated for both SBP and DBP. This process was repeated for all features. The set of features that correspond directly to BP in its two forms (SBP and DBP) were applied to PCA technique. This is an essential procedure to convert the possible correlated features into independent feature sets. The most important features that have the highest correlation with the BP were determined.

A. Singular Value Decomposition (SVD)

In this section, the theoretical background for the PCA techniques that have been used in signal processing procedure, is presented. With this technique, any matrix A of size $M * N$, where M is the number of samples and N is the number of features, can be decomposed into three matrices.

$$A = U\Gamma V^T \tag{1}$$

where U is an M*N matrix, V is n*n matrix and Γ is n* n matrix. The entries of Γ matrix are zeros or positive elements, and they are called singular values. The columns of U are an eigenvector of matrix A.

The matrix A can be defined as AA^T or as A^TA

$$AA^T = U\Gamma V^T V\Gamma U^T \tag{2}$$

$$AA^T = U\Gamma^2 U^T \tag{3}$$

$$A^TA = V\Gamma^2 V^T \tag{4}$$

AA^T is an $n * n$ and A^TA is an $m * m$ dimension.

TABLE I
SUBJECT'S DEMOGRAPHIC DATA

Physical Index	Statistical Data	
Gender	Male (23)	Female (16)
Age (years)	50.4± 16.4	59.1±10.8
Height (cm)	172.6± 6.3	163.5±8.4
Weight (kg)	85.4 ± 14.4	85.5±16.1
Body Mass Index (kg/m^2)	28.7 ± 4.6	32.1±6.4
SBP (mm Hg)	128.5 ± 14.3	135.25±22.9
DBP (mm Hg)	80.2 ± 9.7	80.8±8.1
Heart Rate (beats/min)	85.3 ± 13.6	83.6±10.5
Hypertension	43.5%	25%

Using the previous decomposition, the columns of V and the squared diagonal elements of Γ are represented, as well as the eigenvectors and eigenvalues for AA^T, respectively. The square of singular values equals an eigenvalue in the covariance matrix which is equal to the principal component.

In PCA, the directions in the data with the most variation are determined, i.e. the eigenvectors which correspond to the largest eigenvalues of the covariance matrix, and the projection of the data onto these directions. The singular values in the diagonal matrix Γ can be used to understand the amount of variance explained by each of the singular vectors. The dimensionality reduction can be achieved by simply reducing the number of data, which will cause decrease the computation time and enhance the performance of the overall process. The steps below describe the application of SVD algorithm on the collected dataset:

1. Extracting the features of the PPG signal (as stated before).
2. Determining the SVD (sub matrices $U\Gamma V^T$) matrices, for PPG features.
3. Calculating the number of eigenvectors representing 95%

of the variation.

4. Obtaining the norms of each vector in the new space.
5. Finding the largest two eigenvalues.

The results obtained by the PCA technique show that the stiffness index mean and standard deviation for the heart rate per segment are the most important features. Results are shown in (5) and (6). For the SBP, the best-fit regression polynomial represents the model built for both significant features as shown in (5):

$$SF\ (X,Y) = p_{00} + p_{10} * x + p_{01} * y + p_{20} * x^2 + p_{11} * x * y + p_{02} * y^2 + p_{30} * x^3 + p_{21} * x^2 * y + p_{12} * x * y^2 + p_{03} * y^3 + p_{40} * x^4 + p_{31} * x^3 * y + p_{22} * x^2 * y^2 + p_{13} * x * y^3 + p_{04} * y^4 + p_{50} * x^5 + p_{41} * x^4 * y + p_{32} * x^3 * y^2 + p_{23} * x^2 * y^3 + p_{14} * x * y^4 + p_{05} * y^5 \quad (5)$$

$p_{(i,j)}$ represents the coefficients in (5) with 95% confidence bound.

For the DBP, the best-fit regression polynomial represents the model built for both significant features as shown in (6):

$$SF\ (X,Y) = p_{00} + p_{10} * x + p_{01} * y + p_{20} * x^2 + p_{11} * x * y + p_{02} * y^2 + p_{30} * x^3 + p_{21} * x^2 * y + p_{12} * x * y^2 + p_{03} * y^3 + p_{40} * x^4 + p_{31} * x^3 * y + p_{22} * x^2 * y^2 + p_{13} * x * y^3 + p_{04} * y^4 + p_{50} * x^5 + p_{41} * x^4 * y + p_{32} * x^3 * y^2 + p_{23} * x^2 * y^3 + p_{14} * x * y^4 + p_{05} * y^5 \quad (6)$$

$p_{(i,j)}$ represents the coefficients in (6) with 95% confidence bounds.

The surface fitting that describes the formula of the systolic and DBP are shown in Figs. 5 and 6, respectively. Surface fitting is used to best fit the series of data which are the features that had been determined. The results show that the error value in estimating the SBP is 4.95% and estimating the DBP is 3.99%.

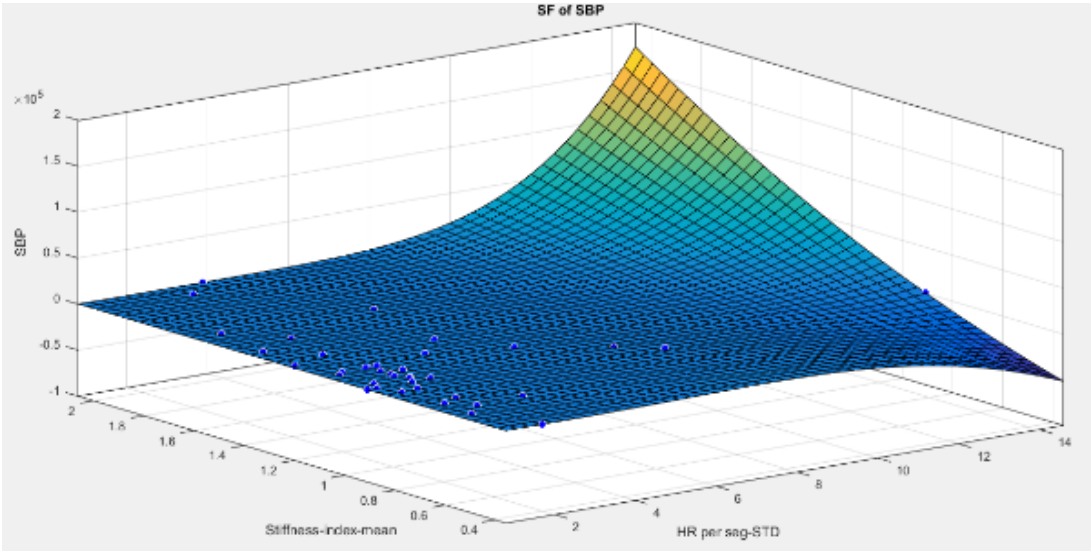

Fig. 5 Surface fitting of the PPG signal for SBP

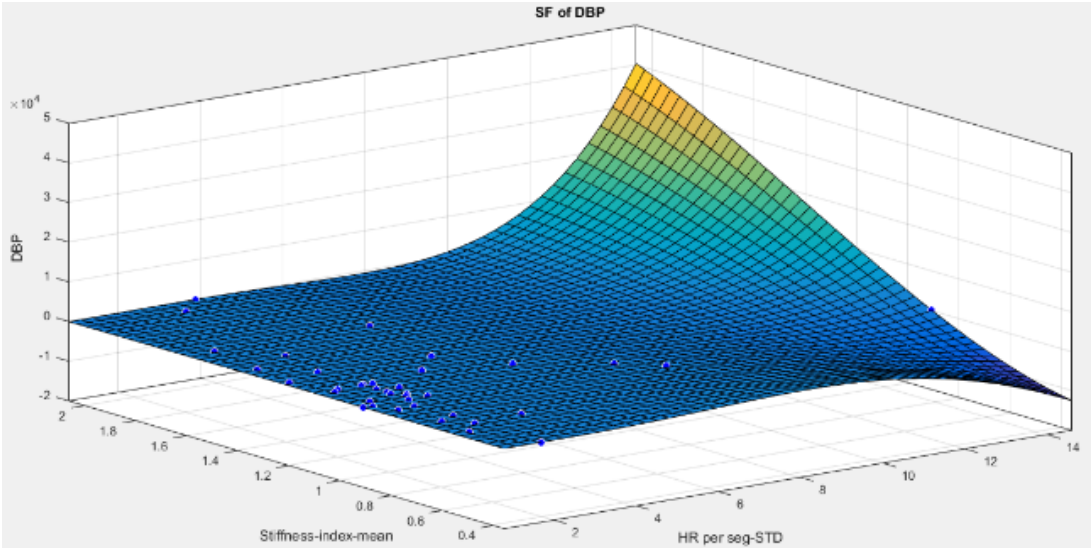

Fig. 6 Surface fitting of the PPG signal for DBP

V. Conclusion

In this paper, a system was designed to measure the PPG signal targeting BP measurement. The PPG signals were studied and the most important features were extracted. The extracted features, as a result of signal processing and segmentation, were applied to PCA to find the important independent feature that correlates with BP. The classified features obtained as a result of the PCA technique showed that the stiffness index mean and standard deviation for the heart rate per segment are the most important features. Both features have been used to estimate DBP and SBP values with an error of less than 5%.

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