An Innovative Method for Continuous, Non-Invasive Blood Pressure Monitoring Using ECG Signals

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Abstract

Information gathered from a wide range of physiological signs may help in both disease prevention and diagnosis. It is very helpful to monitor cardiovascular sickness with frequent blood pressure readings. Modern methods of monitoring blood pressure mostly entail obtaining measurements from the upper arm. Inaccurate measures might result from the patient's uneasiness, which could tighten their arms. An electrocardiogram (ECG) shows the heart's electrical activity and also shows the patient's blood pressure. In this study, we aim to extract features associated with blood pressure from ECG data using a new non-invasive method of detecting blood pressure that uses algorithms based on artificial neural networks to calculate blood pressure values from EKG parameters. The average rate of inaccuracy for the blood pressure readings in this study was less than 5% when compared to the standard equipment. The proposed method relieves the patient of some of the stress associated with continuous blood pressure monitoring by decreasing the possibility of errors caused by the patient's discomfort. This technology could have a lot of useful lessons for the healthcare business.

Introduction

Diseases may be prevented and diagnosed using data from a variety of physiological indicators. Particularly, cardiac arrhythmias may be directly seen. Vascular disorders by monitoring BP on a regular basis. The most used technique of taking blood pressure now measures the pressure in the upper arm. Subject discomfort and tense arm muscles might introduce measurement inaccuracy while taking blood pressure. In the past, researchers have estimated blood pressure and heart rate noninvasively using a photoplethys mogram (PPG) and machine learning approaches.

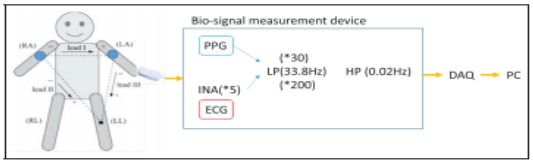


Figure 1. The bio-signal measurement device.

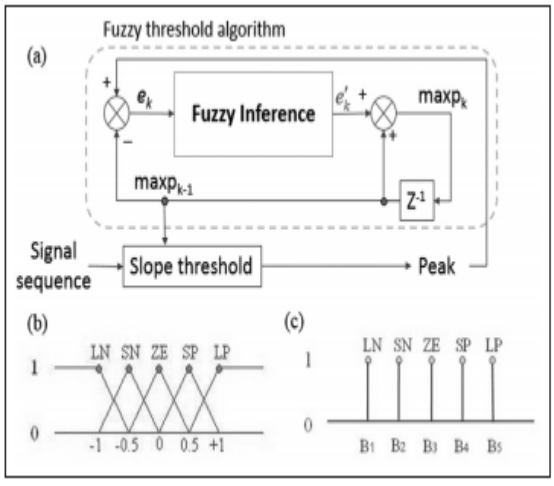
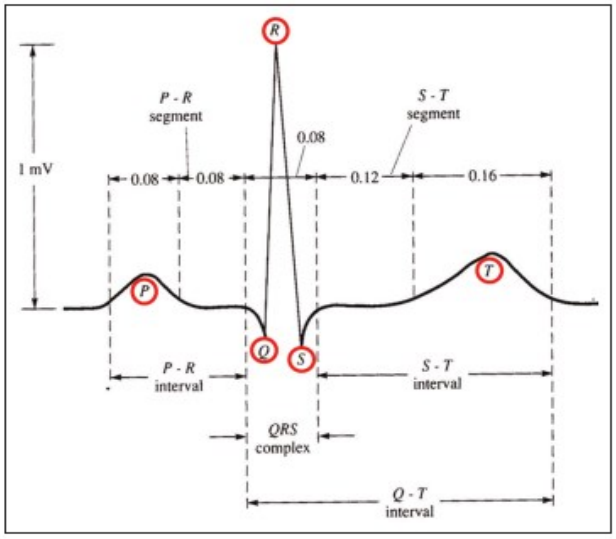


Figure 2 shows the three components of a fuzzy threshold algorithm: (a) the algorithm's structure, (b) the fusilier's membership function, and (c) the defuzzifier's membership function.



Glucose level (BGL), systolic blood pressure (SBP), and diastolic blood pressure (DBP) are shown in Figure 3 as the wave segment parametric of a normal ECG.#1 Temporal-spatial Heart rate (HR) and blood pressure (BP) are two examples of non-stationary cardiovascular oscillations that are often analyzed using time-frequency (T-F) analysis. Previous research has employed the T-F recursive autoregressive method to examine PTT variability; PTT is a cardiovascular measure of growing interest because of its potential to provide continuous, non-invasive estimates of blood pressure (BP). Recent research indicates that PTT is connected to both SBP and HR.2 In addition to displaying PPG and BP data, an electrocardiogram (ECG) also depicts the electrical activity of heart function. An oscillometric signal may be polluted with noise and artifacts, but a better quality and more consistent ECG signal makes it easier to distinguish real cardiac pulses, increasing the reliability of the BP estimate.3

It was suggested, for instance, that an ECG signal may be used to rebuild an oscillometric signal that had been tainted by artifacts, allowing for a more precise measurement of blood pressure.4 In a similar vein, the accuracy of blood pressure readings was improved by using synchronized ECG signals to filter out motion aberrations from oscillometric data.5 Heart rate (HR) and heart rate variability (HRV) are two ECG characteristics the doctor may use to evaluate a patient with cardiovascular disease and perhaps prevent an acute myocardial infarction or myocardial ischemia. It has been hypothesized that the PPG signal may be used to estimate BP. Both standalone PPG-based approaches6, 7 and combined PPG- and ECG-based approaches exist.8–11

To streamline the measuring procedure and save valuable time, we suggest using a single physiological signal to determine many physiological parameters. This research leverages artificial neural network algorithms to estimate BP readings from ECG data, allowing for a novel non-invasive BP measurement technique to be developed.

Methods and implementation

Instrumentation for measuring biological signals: its design The PPG and EEG were measured using a bio-signal measuring apparatus (Figure 1) we developed specifically for this purpose. ECG at once, with a sampling rate of 100 Hz, and concurrently storing the raw data on a computer.

Online PPG and ECG peak detection

QRS complexes in ECG recordings and peaks and valleys in PPG sequences were localized using so and Chan's12 technique. In real time, as seen in Figure 2(a), the fuzzy thresh old method modified the slope threshold. Time features (Figure 3) between each wave and the R wave in ECG recordings allowed us to identify the additional peaks (P, Q, S, and T) of the ECG when the QRS complexes were identified.

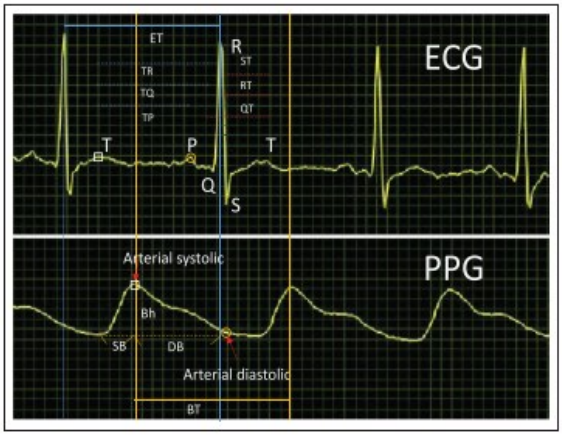


Figure 4. The relationship between ECG and PPG.

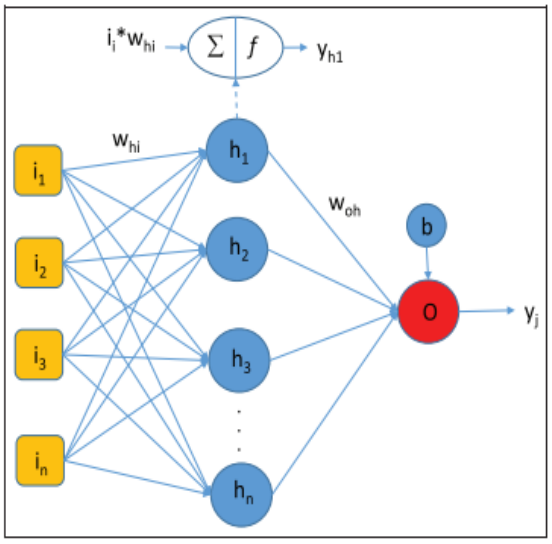


Figure 5. The intelligent neural network structure.

Table 1. Fuzzy inference rule table.

e_k	LN	SN	ZE	SP	LP
e'_k	LN	SN	ZE	SP	LP

LN: negative large; SN: negative small; ZE: zero; SP: positive small; LP: positive large.

Sequences. Similar results were found for PPG's peak. Here we detail the technique used for detecting fuzzy peaks.

Let the ECG amplitude at time k be denoted by X (k). Time k is separate. Using Equation (1), we can get the angle of the ECG wave.

$$\text{slope(k)} = -2X(k-2) - X(k-1) + X(k+1) + 2X(k+2) \quad (1)$$

$$\text{slope\_threshold} = 1/2 \times \max p_k \quad (2)$$

The first 200 readings from an electrocardiogram (ECG) are used to determine the initial maxp.

When the conditions for two consecutive ECG readings are met, the onset of the QRS complex is identified when slope (k) is larger than the slope threshold specified by equation (2). Once the QRS complex has been identified, the maximum point (maxp) is located and used as the R point. The fuzzy threshold technique, described by equations (3) and (4), and then adjusts the maximum probability.

$$\max p_k = \text{fuzzy}(\text{peak} - \max p_{k-1}) + \max p_{k-1} \quad (3)$$

$$\text{peak} = \text{height of } R \text{ point} - \text{height of } QRS \text{ onset} \quad (4)$$

As an input to the fuzzy threshold method, the difference between peak and maxpk21 generates a prediction error, denoted by the symbol "ek." Expressed as a formula (5)

$$e_k = \text{peak} - \max p_{k-1} \quad (5)$$

Equation (6), where Si is the membership grade, is the fuzzy threshold's center-of-gravity calculation for its output variable (e9k). In where Pi is the middle value of the it premise and Bi is the middle value of the it conclusion. (Figure 2(c)) The defuzzifier operates on a scale from B1 to B5.

$$e'_k = \frac{\sum_{i=1}^{n} S_i B_i}{\sum_{i=1}^{n} S_i} \quad (6)$$

Consideration of the PPG-ECG Connection

In order to convert the ECG signal into a blood pressure reading, the correlation between each factors for the transformation by combining the arterial systolic and artery diastolic wave segments (Figure 4). Similar to TQ and TP, "TR" in Figure 4 denotes the time interval between the T wave and the subsequent cycle of the R wave. "ST" denotes the time between the S wave and the T wave in the same cycle, much as "RT" and "QT. The letters "SB" represent the systolic phase of the heart's beat, whereas "DB" represents the diastolic phase. The letters "ET" stand for the R-R interval period of an electrocardiogram, while "BT" denote the PPG cycle.

$$f(x) = 1/\exp(-0.5x) \quad (7)$$

Equation (8), where f is the activity function, netjn is the number of synapses between the nth and jth neurons, and ynj is the output of the nth layer and jth neuron, describes the interlayer processing of the EBP. The n21layerweightaccumulatedvalue. The output of the kth neuron in the output layer (yk) is used to calculate the error function (E), which is defined as (9), where dk is the kth target value.

Where p is the number of times trainee p has gone through training, we may use equations (10) and (11) to fine-tune the weight value.

$$y_j^n = f\left(net_j^n\right), \quad net_j^n = \sum_i w_{ji}^n y_i^{n-1} + b_j^n \qquad (8)$$

$$E = \frac{\sum_k (d_k - y_k)^2}{2} \qquad (9)$$

$$w_{ji}(p) = w_{ji}(p-1) + \Delta w_{ji} \qquad (10)$$

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} = -\eta\left(d_j - y_j^n\right) f'\left(net_j^n\right) y_i^{n-1} \qquad (11)$$

Examining the GUI for flaws

In order to create an ECG analysis platform, this research used MATLAB's GUI. As seen in Figure 6. This system's capabilities, such as peak detection, ECG analysis, and blood pressure estimation, will be shown.

Result

Measurement experiments

Throughout this investigation, we entered in ECG, PPG, and BP readings (Figure 7). The Procedures Involved in Signal Processing

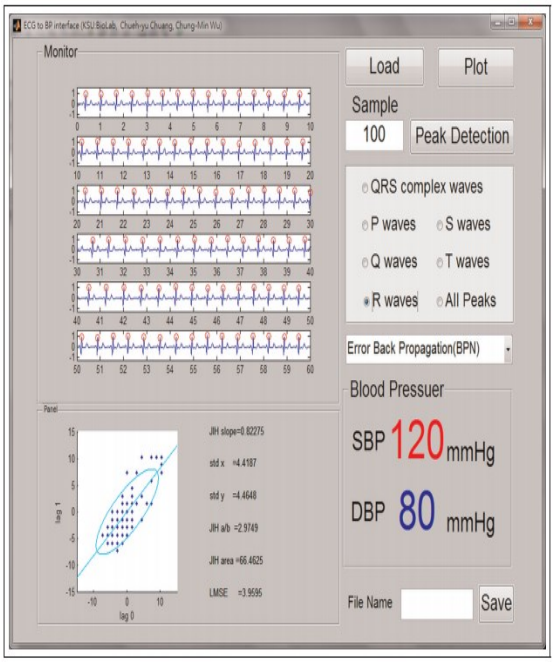
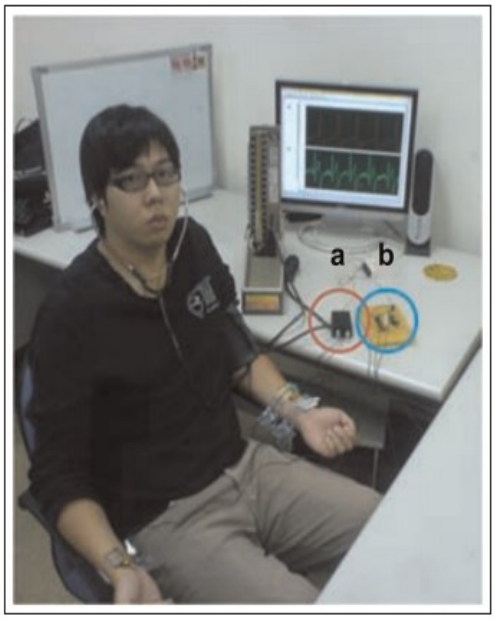


Figure 6. The analysis platform for the ECG signal.



The electrocardiogram (ECG) and photoplethysmograph (PPG) were used to acquire the experimental data shown in Figure 7.

Identifying signal peaks, correlating results, and worked out the optimal parametric connection between these signals. Figure 8 depicts the ECG and PPG peaks identified by the fuzzy threshold technique. In Figure 8(b) and (d), the dotted line represents the peak detection threshold. Peaks in the PPG are shown in Figure 8(c), where the threshold for peak identification is set at 50% of the PPG's maximum amplitude.

Examining ECG and PPG Traits

In order to determine the commonalities between electrocardiograms and electroencephalograms, we first gathered data from five people. Analyzing the correlation between the ECG and PPG data after processing is displayed in Table 2. For the input variables into the neural network, we chose the parameters of the intervals ET, RT, QT, ST, TP, TQ, and TR that were more than 68.2% (one standard deviation).

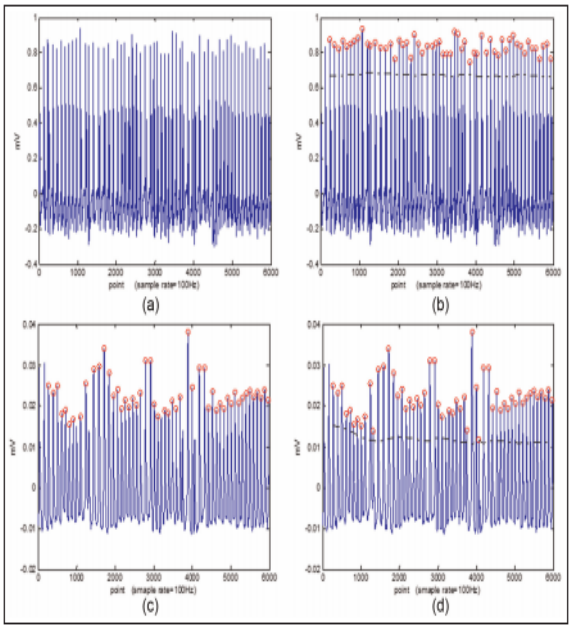


Figure 8: A comparison of raw and fuzzy data for peak detection in ECGs and PPGs. Raw ECG data (a), Fuzzy ECG R wave peak detection (b), Peak Potential Gyroscope (PPG) data (c), and Fuzzy PPG peak detection (d).

The illustrative correlation study of ECG and PPG data is shown in Table 2.

PPG	BT	Bh	SB	SB	SB	DB	DB	DB
ECG	ET	Rh	RT	QT	ST	TP	TQ	TR
Subject 1	0.98	−0.2	0.8	0.88	0.8	0.94	0.96	0.96
Subject 2	0.97	0.26	0.68	0.75	0.74	0.95	0.96	0.96
Subject 3	0.92	−0.04	0.81	0.79	0.83	0.86	0.85	0.86
Subject 4	0.98	−0.1	0.67	0.7	0.56	0.82	0.91	0.9
Subject 5	0.99	−0.04	0.81	0.74	0.76	0.84	0.85	0.85
Average	0.97	−0.02	0.75	0.77	0.74	0.88	0.91	0.91

PPG: photoplethysmogram; ECG: electrocardiogram.

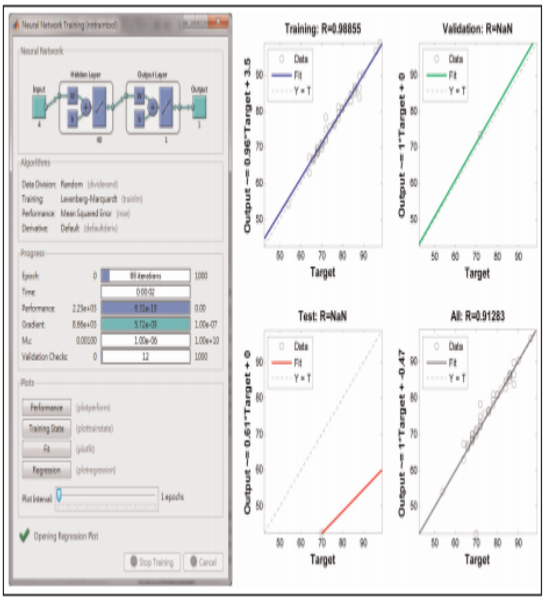


Figure 9. The training performance of the neural network.

Estimated value of BP

In this research, two back-propagation neural networks were created using the ET, RT, QT, ST, TP, TQ, and TR time segments as input. Four-input, forty-hidden, one-output architectures. Using ET, QT, RT, and ST as input, one block calculated the SBP, while another calculated the DBP using ET, TP, TQ, and TR as input. Fifty people between the ages of 20 and 26 participated in the research, and two datasets were obtained from each of them, for a total of one hundred. There were a total of 100 datasets utilized; 50 for training and 50 for testing. Appendix 1 shows the results of a comparison between the estimated value of BP (ECG-BP, PTT-BP) and the value of the mercury sphygmomanometer (KENLU model K-300), which was learned using 50 datasets (Figure 9). The ECG-BP model has an average error rate of 1.96% for the estimated SBP and 2.14% for the estimated DBP. In the PTT-BP model, the average error rate for the estimated SBP was 6.23 percent, while the average error rate for the calculated DBP was 6.23 percent.

Conclusion

When compared to the KENLU model K-300 mercury blood pressure monitor, the average error rate of the BP measurement was less than 5% in this research (1.96 percent for SBP and 2.14 percent for DBP). External environmental and behavioral variables, as well as the body's own cardiovascular regulating systems, may all have an impact on blood

pressure. In order to estimate the BP value in real time, the back-propagation neural network makes use of a supervised learning method that can track fluctuating HR with user behavioral change. In conclusion, the results of this investigation may be used to the monitoring of BP fluctuations, and the suggested technique can be utilized to continually monitor BP with little stress. Instead of simultaneously monitoring the ECG and PPG, this research used the ECG bio-signal to estimate the BP value using a signal measurement apparatus that minimizes interference from high-frequency noise and motion aliasing. The ECG-BP model developed in this article outperforms the PTT-BP model11 shown in the appendix. The medical field stands to benefit greatly from this technology.

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