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ORIGINAL ARTICLE

A new approach for blood pressure estimation based on phonocardiogram

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Abstract
Continuous and non-invasive measurement of blood pressure (BP) is of great importance particularly for patients in critical state. To achieve continuous and cuffless BP monitoring, pulse transit time (PTT) has been reported as a potential parameter. Nevertheless, this approach remains very sensitive, cumbersome and disagreeable in ambulatory measurement. This paper proposes a new approach to estimate blood pressure through PCG signal by exploring the correlation between PTT and diastolic duration (S21). In this purpose, an artificial neural network was developed using as input data: (systolic duration, diastolic duration, heart rate, sex, height and weight). According to the NN decision, the mean blood pressure was measured and consequently the systolic and the diastolic pressures were estimated. The proposed method is evaluated on 37 subjects. The obtained results are satisfactory, where, the error in the estimation of the systolic and the diastolic pressures compared to the commercial blood pressure device was in the order of 6.48 ± 4.48 mmHg and 3.91 ± 2.58 mmHg, respectively, which are very close to the AAMI standard, 5 ± 8 mmHg. This shows the feasibility of estimating of blood pressure using PCG.

Keywords Blood pressure · Systolic duration · Diastolic duration · Phonocardiogram signal PCG · Pulse transit time PTT

1 Introduction

Blood Pressure (BP) including systolic blood pressure (SBP) and diastolic blood pressure (DBP) is an important and vital sign of health care. SBP is the peak pressure in the arteries when the blood flows from the ventricles to the arteries during ventricular systole, and DBP is the minimum pressure in the arteries during ventricular diastole when the ventricles are full of blood. BP can be measured both invasively and non-invasively,using or not using cuff, non-continuously and continuously. Instantaneous BP measurement can only momently reveal physiological status, while the continuous BP measurement provides continuously physiological status which can be used for predicting risk of serious cardiovascular events and making antihypertensive therapy decisions [1]. Therefore, the continuous, cuffless and non-invasive blood pressure estimation based on the pulse transit time (PTT) has gained increasing attention in recent years [2].

The PTT is the time taken by a one pulse wave to travel a distance between two site in the body . Usually the heart is considered as the starting point and the index as the ending point. To achieve this measurement, two systems are needed: An Electrocardiograph (ECG) and a Photoplethysmograph (which detects the PPG signal). In the ECG signal, the peak R corresponds to the contraction of the ventricles and propulsion of blood in the arteries. It is considered as the starting point for PTT measurement. In the PPG signal, the peak (P) of this signal is considered as the ending point in the PTT measurement. The timing difference between the two peaks determines the pulse transit time PTT as presented in Fig. 1. The Blood pressure is then estimated by using some fluid dynamics laws [3]. This method is appreciated in the case of bedridden position. However, its use remains limited in the situation of ambulatory blood pressure measurement, because it requires two different instruments with many

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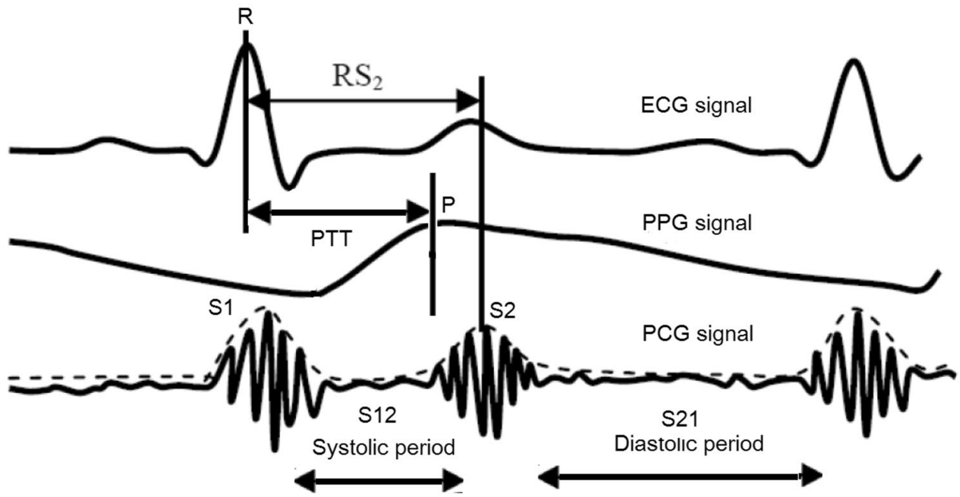
Fig. 1 Simultaneous presentation of the three physiological signals ECG PPG and ECG with the differents temporal parameter used in the estimation of the arterial pressure



sensors (three ECG electrodes and PPG fingertips optical sensor) which are completely disagreeable for patients in routine life.

The necessity to find an alternative solution is of great importance. Among alternative solutions, the Phonocardiographic signal (PCG) gain great interests. This signal represents the recording of the mechanical activity of heart. Generally, through a simple stethoscope two significant sounds can be distinguished (S1 and S2) produced respectively by the closure of the atrio-ventricular valves and sigmoid [4]. The recording and processing of this signal can provide more information about the heart and its physiological behaviour. In the PCG trace (Fig. 1) the fluctuations S1 and S2 indicate respectively the first and second heart sound. The spectral characteristics of these sounds are related directly to the state of the valves and the hemodynamic of blood. The interval S12 indicates the systolic duration, it is the time taken by the ventricle to expulse out the blood. The interval S21 is the diastolic duration, and it is the time taken by the ventricle to be full again. The variation in cardiovascular hemodynamic is reflected directly to various physiological signals, including PCG signal. Therefore, it will be of great importance to find an adequate parameter in this signal which allows a correct estimation of blood pressure.

In the literature, several attempts have been made to achieve this goal. The first was in 1965 by Sakamoto et al. [5], where the dependence of the systolic blood pressure (SBP) with the intensity of the first sound S1 is studied. The results show a good correlation between the systolic pressure peak of left ventricle and the intensity of S1. The analysis of the second cardiac sound S2 was also the subject of several studies. In 2006, Zhang et al. [6] present a study on the relationship between the SBP and the time RS2 delimited by the peak R of the ECG signal and the peak of the second sound S2 of PCG signal (see Fig. 1). The correlation between the two parameters was acceptable with a correlation coefficient of $R^2 = 0.85$. Recently, in 2017, Dastjerdi et al. [7] propose a new approach for estimating PTT using simultaneously the PCG and the PPG signals and through which they estimate the SBP and the DBP. The obtained results are satisfactory since the corresponding correlation coefficients were equal to 0.84 and 0.86. In the same year, Hsiao et al. [8] propose a new approach for estimating BP using vascular transit time (VTT), defined as the difference in time between S1 and the peak of PPG signal. The results of this study show that for the range of normal blood pressure, the error in systolic blood pressure is 6.67 ± 8.47 mmHg, which is very close to the AAMI standard [9], 5 ± 8 mmHg.

This paper describes a new approach to estimate blood pressure through PCG signal by exploring the relationship between PTT and both systolic (S12) and diastolic (S21) durations. We started with the hypothesis that if the physiological signals (PCG, ECG and PPG) are correlated together and if PTT (obtained from ECG and PPG) is linearly related to systolic blood pressure, then, certainly there is a relation between PCG signal and blood pressure. Also, if RS2 and PTT depends on systolic pressure, then, RS2 (which is systolic duration) should be in relation with PTT. The methodology followed to prove this hypothesis is presented in below.

2 Methodology

To study the relationship of BP to PCG signal, this paper is subdivided on two parts. The first concerns the processing of PCG signal in order to extract the systolic and the diastolic durations and study their relationship with a PTT estimated using the hemodynamic laws in the body. Then, the evolution of S12 and S21 according to PTT is explored to find any possibility of a direct estimation of BP. The second part concerns the development of an algorithm based on neural networks to estimate blood pressure from results found in the first part along with number of variables concerning patient such as: Height, Weight, Sex and HR.

The proposed approach is evaluated using a database realised for this purpose. This database contains PCG recordings, SBP, DBP, HR, of 37 subjects Male and female with different body height and weight. All the subjects signed an agreement to voluntary participate to this study. The PCG signals were processed and analysed to measure respectively the systolic (S12) and the diastolic durations (S21). The protocol followed in the experiments consists to take the measurements in sitting position after a resting period of 10 min. This rest time is necessary; it allows the stability of pressure in the body. After the rest time, the PCG signal is recorded for a duration of 10 s (5–6 cycles), then, and in the same position, the blood pressure is measured immediately in the left arm by an electronic sphygmomanometer. This protocol is approved by Jichi Medical University School of Medicine, Tochigi, Japan, where a similar works were published previously [10, 11].

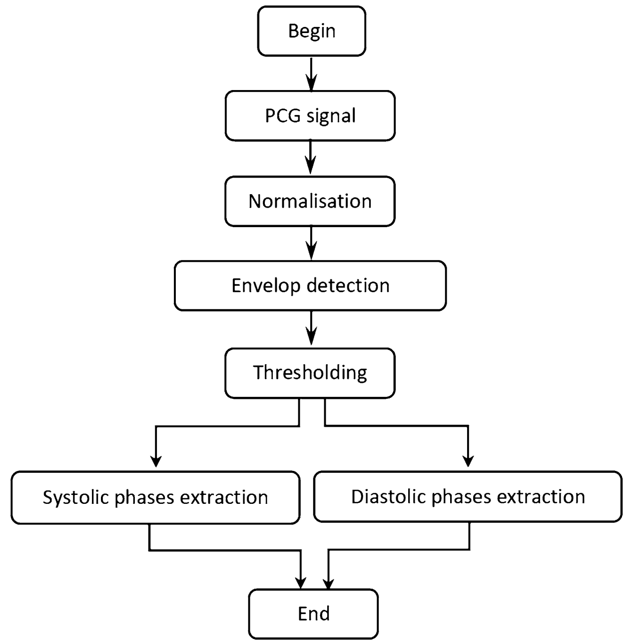


Fig. 2 The organigram of detection and measurement of systolic and diastolic durations

3 Part 1: measurement and processing

3.1 Anthropometry

The body height and weight were measured using an electronic stadiometer scale (precision, 0.1 cm, 0.1 kg). The subjects wearing was light clothing.

3.2 Data collection

The PCG signal is detected through an electronic stethoscope (MTL209) connected via a jack plug to an acquisition system: the PowerLab system (15T, ADInstruments, Australia). It is initially sampled at a frequency of 10khz then low pass filtered at 500Hz.

3.3 BP measurement

The blood pressure is measured using a validated cuff oscillometric device (A130, Microlife, Widnau, Switzerland). It automatically measures and stores the SBP, DBP and HR. Three successive measurements for each subject (after at least 10min of rest in sitting position of the subject) were made after the recording of its PCG signal. The average value of these measurement is used for analysis.

3.4 S12 and S21 measurement

The algorithm used to measure S12 and S21 is illustrated in Fig. 2. It is implemented in Matlab environment. First the detected PCG signal amplitude is normalized to 1, then its envelop is detected using the method of simplicity described in [12]. This approach allows a perfect envelop detection even in the cases of low heart sounds intensity. The next step is a thresholding operation of the detected PCG envelope. For S1/S2 localisation and identification. The threshold is fixed empirically at 0.5. In the last step, the systolic and diastolic phases are extracted and calculated. For more details about these processing steps the reader may refer to reference [13].

3.5 Estimation of pulse transit time (PTT)

The PTT is estimated using the Eq. (1), proposed in reference [14]. The authors state that the Mean Blood Pressure (MBP) can be derived according to PTT, the distance from the heart to the index, the vertical distance between heart and index, blood density and the earth gravitation.

$$MBP(mmHg) = \left(\frac{\rho\, d^2}{1.4\, PTT^2} + \frac{\rho g h}{0.7} \right) 0.0075 \tag{1}$$

where MBP is Mean blood pressure (mmHg), ρ is density of blood ($\simeq$ 1010 kg/m^3), d is distance between heart and index (m), PTT is Pulse transit time (s), g is earth gravitation 9.81 m/s^2, and h is vertical distance between heart and index (m) and the constant 0.0075 is to make a convertion from Pascal unit to mmHg. According to anthropometric segment length of human body [15], the distance d is estimated by

(0.6 ×body height) [14], similarly the distance h is estimated in sitting position by (0.30 × body height).

Finally, by replacing the constants (ρ and g) by their value, the MBP is represented by two variables (PTT and height) as shown by Eq. (2). The PTT can therefore be determined as a function of MBP (Eq. 3).

$$MBP(mmHg) = \frac{1.947\ \text{height}^2}{PTT^2} + 31.84\ \text{height} \tag{2}$$

$$PTT(s) = \sqrt{\frac{1.947\ height^2}{MBP - 31.84\ height}} \tag{3}$$

where PTT is the pulse transit time (s), MBP is the mean blood pressure (mmHg) and height is the subject height (m).

In our study, the mean pressure (MBP) is calculated where DBP and SBP are measured by a sphygmomanometer.

$$MBP(mmHg) = \frac{2}{3}DBP + \frac{1}{3}SBP \tag{4}$$

So, the PTT is determined using Eq. (3) in sitting position by measuring the height and the MBP for each subject of the database.

3.6 Statistical analysis

All data are expressed as the mean±SD or percentage. The differences in SBP, DBP, S12, and S21 measured for the same subject are compared using paired t-tests. the significance level, $p < 0.05$. The relationship between PTT and S12 or S21 is assessed by the R^2 correlation coefficient. All statistical analysis is performed using OriginLab v8.

3.7 Results

The age of the subjects in the present study ranged from 22 to 40 years (mean ± SD: 26.10 ± 6.36 years) and there were 27 males and 10 females. The majority of the subjects are in good health, except for a few cases with mild hypertension (4 cases), and without following any particular medication. The characteristics of the subjects participating to this study are resumed in Table 1.

Figure 3 shows obtained signals and parameters illustrating the successive steps of the proposed algorithm to get to the measurement of the systolic and diastolic durations. These obtained results, along with calculated and/or measured parameters (SBP, DBP, MBP and PTT) are resumed in Table 2 below.

Figure 4 illustrates the obtained results of the correlation analysis between respectively S12-S21 and PTT. Figure 4a, b illustrates respectively the distribution of the systolic duration (S12) according to PTT and that of the diastolic duration (S21) according to PTT. For the former, one can notice that there is no particular distribution whereas for the latter a particular distribution of two classes is observed as it is clearly depicted in Fig. 5.

Table 1 characteristics of the subjects participating in this study

Patient characteristics (N = 37)	
Age (years)	26.10 ± 6.36
Gender (% male)	73
Height (cm)	174.59 ± 7.38
Weight (Kg)	70.97 ± 14.45
Healthiness	
Good health (%)	94.6
Mild hypertension (%)	5.4

The best fitting curve of each class is found to be an exponential function ($y = a\,x^b$) with correlation coefficient R^2 = 0.84 and 0.94 for respectively class 1 and class2. As illustrated on Fig. 5.

This result let us think the possibility of estimating the PTT then MBP if an appropriate equation linking PTT to S21 can be found. Therefore, it was necessary to find out an adequate parameter able to establish a separating rule for these classes. To eventually achieve this aim, a comparative study between these two classes according to the height of the subject, the weight of the subject, the systolic duration, the diastolic duration and heart rate was carried out. However, according to the obtained results none of these parameters seems to be able to make a significant separation [16]. To solve this problem an artificial neural network was developed.

4 Part 2: artificial neural network modeling

The idea is to apply all measured parameters (S12, S21, Height, Weight, Sex and HR) to the input of a neural network, from which a decision (class1, class2) will be taken. According to this decision, an equation can be developped for estimating PTT and consequently deducting MBP. The organigram illustrating this process is presented on Fig. 6. To achieve this goal, each data is labeled to its membership class (either class 1 or 2) according to the result illustrated on Fig. 5, this labeling is necessary for training and testing of the NN. In order to predict the classification decision, six parameters are used as inputs to the neural network. These are: sex, height, weight, heart rate, systolic duration (S12) and diastolic duration (S21). The NN processes all these

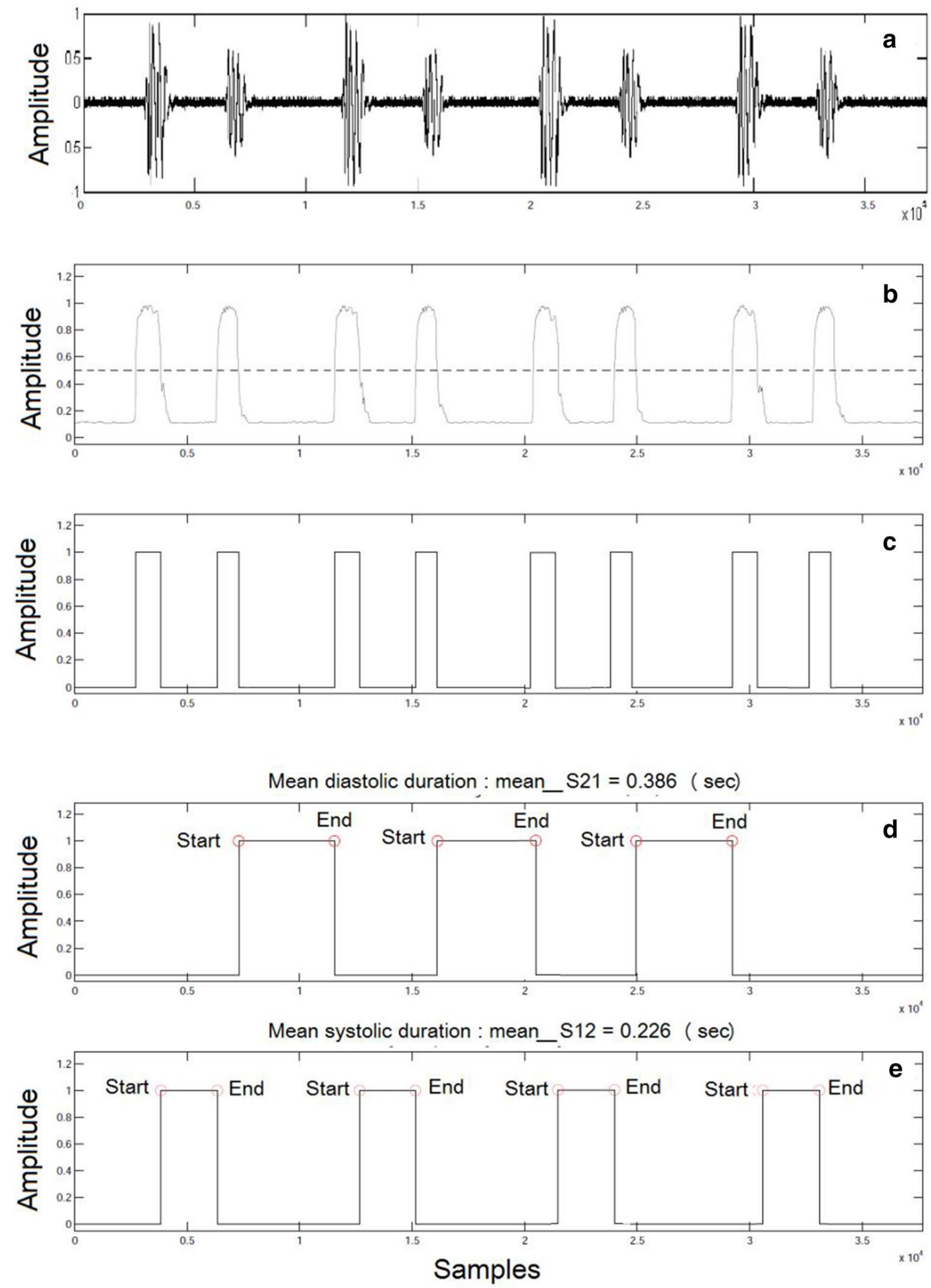


Fig. 3 The result of the different steps of the segmentation algorithm. **a** The recorded PCG signal, **b** the detected envelop of PCG signal, **c** the maximisation of the envelop between [0,1] after thresholding operation, **d** the extracted diastolic phases with the mean duration value and **e** the extracted systolic phases with the mean duration value. The amplitude unit of the PCG signal in **a** is Volt normalised, the others amplitude on b, c, d and e have not a particular unit

Table 2 Result of the measurement of the different parameters

Measured parameter	Mean ± SD	*p* value
SBP (mmHg)	123.27 ± 13.31	< 0.001
DBP (mmHg)	77.43 ± 9.52	< 0.001
MBP (mmHg)	92.71 ± 9.76	< 0.001
HR (bpm)	68.51 ± 11.49	< 0.001
S12 (ms)	0.31 ± 0.02	< 0.001
S21 (ms)	0.59 ± 0.13	< 0.001
PTT (ms)	408.46 ± 50.72	< 0.001

inputs to take one decision which can be class 1 or class 2. In this system, the feedforward multilayer perceptron neural network was used for modeling the classifier of our system [17].

Developing an ANN involves three steps. The first step is developing the data required for network training. The second step is evaluating different neural network structures in order to select the optimal one. Finally, the third step is testing the neural network using data not previously used in network training.

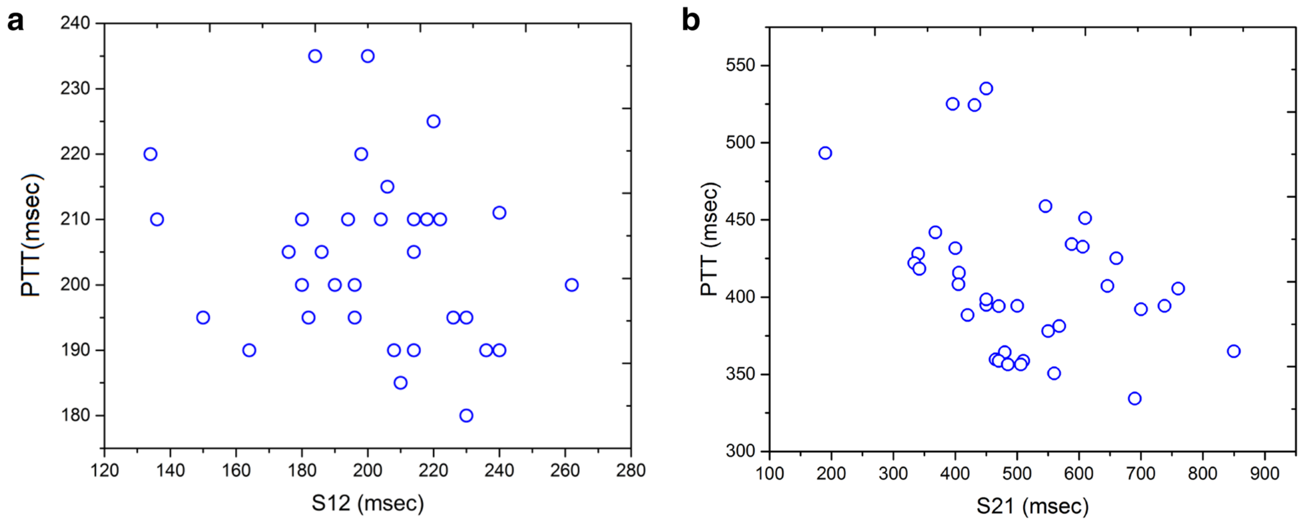


Fig. 4 The distribution of diastolic and systolic durations according to pulse transit time PTT. **a** S12 versus PTT, **b** S21 versus PTT

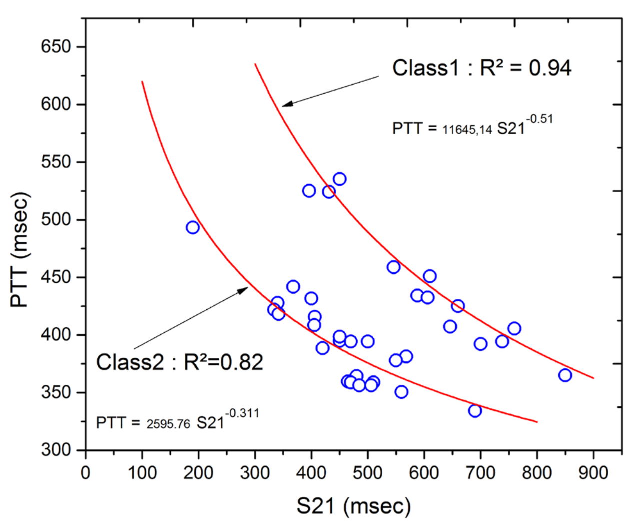


Fig. 5 The distribution of diastolic duration with the estimated PTT, and the approximation curve for each class

The measured or calculated data from the 37 subjects are subdivided in three groups, where two are used for network training, while the remaining group is used for network testing. By swapping the groups (see Fig. 7) between the network training and testing, three tests were carried on. This cross-validation allows to find the optimal NN structure of our system.

For more precision, all inputs data were normalized in [0, 1] intervals. Also, the sex input is declared on binary (0 for female and 1 for male). Similarly, the output vector is declared on binary (0 for class1 and 1 for class2). The neural network structures evaluated are composed of three layers (input layer, one hidden layer and output layer). By varying the number of neurons in the hidden layer (from 2 up to 8) seven structures were tested. For each of the structures, the activation function used in each hidden layer neuron was the sigmoid function. While, the step activation function was used in the output layer. This function allows getting binary output (0,1) which is adapted perfectly to our classification. The stopping criteria of the training algorithm is fixed empirically by two conditions, either MSE = 10^{-4} or 10,000 iterations using the back-propagation algorithm [18]. The NN structure producing the smallest MSE is considered as the most optimal one. In the testing phase, the three combinations presented on Fig. 7 were used.

After ANN classification of all data to their appropriate classes, the second step was the estimation of PTT using the equations for class 1 and class 2 given in Fig. 5. Then, the mean blood pressure is estimated using eq.2.

The systolic and diastolic pressure are estimated using the approximation formulas relating both SBP (Eq. 5) and DBP (Eq. 6) to MBP proposed by Tozawa et al. [19]. These formulas have been proposed empirically after a study of a large database of more than 10000 subjects. This study consisted on the analysis and the evaluation of the correlation of the respective measured SBP,DBP and MBP of each subject.

$$SBP = 1.3\ MBP + 1.5 \tag{5}$$

$$DBP = 0.83\ MBP - 0.7 \tag{6}$$

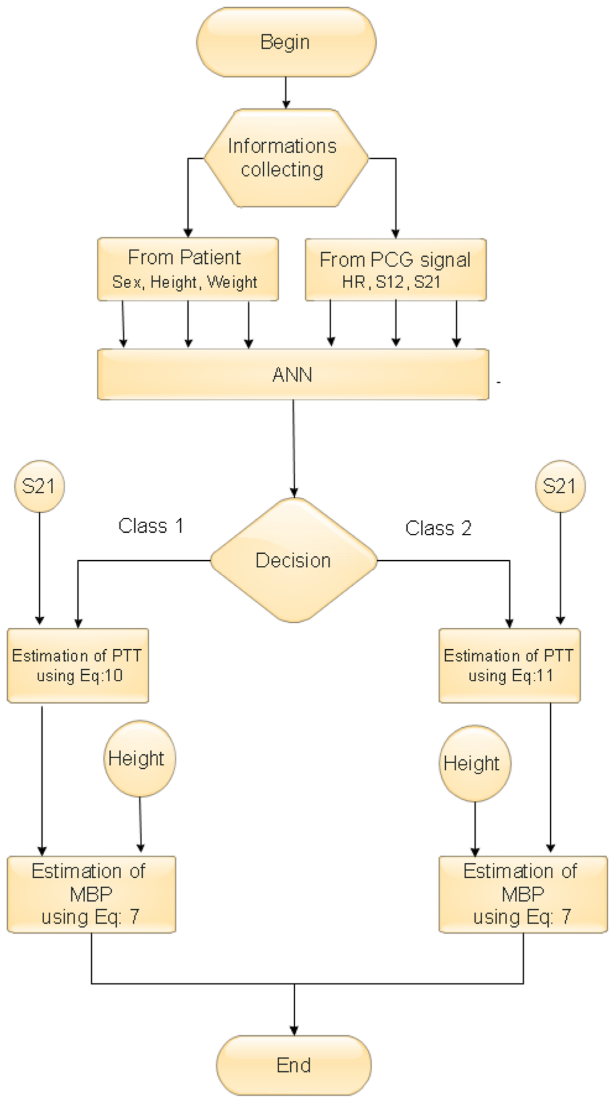


Fig. 6 The organigram used for estimating MBP through PCG signal

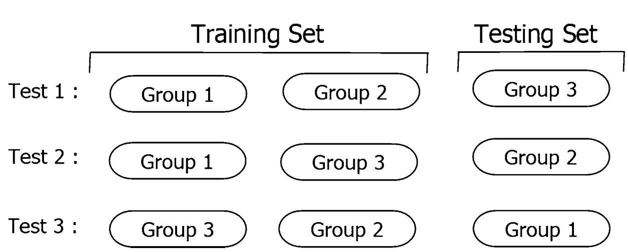


Fig. 7 The different test done to validate the optimal neural network

4.1 Results

Table 3 presents the overall performance (success rate), training and testing of each network. It can observed that the ANN with four neurons in the hidden layer (in bold) has a

Table 3 The structure of the neural network used in this work

Number of hidden layer neurons	Test 1			Test 2			Test 3			Mean success rate
	MSE			MSE			MSE			
	Training	Testing	Success rate (%)	Training set	Testing set	Success rate (%)	Training set	Testing set	Succes rate (%)	
2	0.036	0.316	66.67	0.038	0.216	75.00	0.065	0.0528	91.67	77.78
3	0.036	0.331	58.33	0.04	0.144	83.33	0.08	0.0118	100.00	80.56
4	**0.00019**	**0.0043**	**100.00**	**0.000194**	**0.0155**	**100.00**	**0.000198**	**0.01**	**100.00**	**100.00**
5	0.04	0.244	66.67	0.04	0.172	83.33	0.08	0.023	91.67	80.56
6	0.04	0.2087	75.00	0.04	0.167	83.33	0.08	0.015	100.00	86.11
7	0.0001985	0.217	66.67	0.0005515	0.124	75.00	0.000198	0.046	91.67	77.78
8	0.04	0.197	75.00	0.0401	0.17	83.33	0.08	0.1069	91.67	83.33

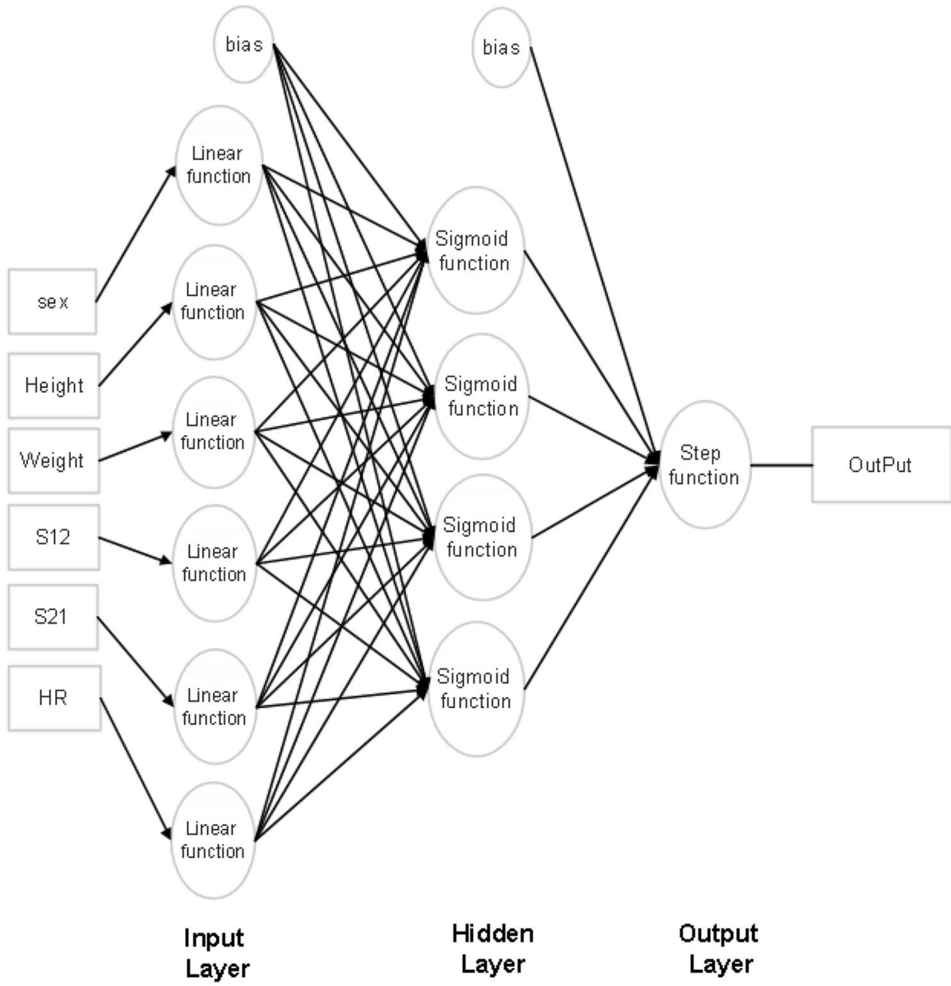


Fig. 8 The structure of the neural network used in this work

minimum MSE and a 100% success rate for each of the three tests (test1, test2 and test3). This structure (given in Fig. 8) is therefore selected as the optimal for classifying our data.

Table 4 resumes the results of the comparing evaluation of the PTT predicted by the proposed algorithm and that measured. The Criteria used for this comparing evaluation are absolute error (MAE), the Mean relative error, the Standard deviation (STD) and the correlation coefficient (R^2). According to this table, the class1 MAE and MRE value's found are 2.49 ms and 2.75%, respectively. These values illustrate the high resemblance between the predicted PTT values and that measured. This result is also emphasized by the high correlation coefficient $R^2 = 0.94$ obtained through the correlation of the predicted PTT and that measured.

In the case of class2, the MAE and MRE values found are 14.14 ms and 3.65%, respectively. In this case the MAE is higher than that of class 1, whereas MRE remains comparatively low. As for class 1, the predicted PTT values resemble that of the measured PTT. This is also confirmed by the High correlation coefficient $R^2 = 0.81$.

Figure 9 represents the regression plot between the measured MBPs (obtained by the sphygmomanometer) and the predicted MBPs (obtained by our algorithm) of all 37 subjects, where a high correlation coefficient ($R^2 = 0.92$) is obtained.

Table 5 resume the SBP and the DBP values estimated using the proposed algorithm. In the case of the systolic pressure, it can be observed a significant Absolute Error (AE) exceeding 10 mmHg in 7 cases. Whereas, in 10 cases, the SBP is estimated with AE varying error between 5 and 10 mmHg. However, for the remaining cases (20 cases) the obtained AE is less than 5 mmHg. Overall, the MAE found in the estimation of SBP is 6.48 mmHg with a STD of

Table 4 The result of PTT's found by the algorithm for each class

Class 1					Class 2				
Subjects	PTT (ms)				Subjects	PTT (ms)			
	Experimental results	ANN prediction	Absolute error	Relative error		Experimental results	ANN prediction	Absolute error	Relative error
1	525.17	551.23	26.06	4.73%	14	394.39	375.74	18.65	4.73%
2	434.24	450.58	16.34	3.63%	15	395.05	388.25	6.80	1.72%
3	407.35	429.47	22.13	5.15%	16	431.66	402.74	28.92	6.70%
4	535.17	516.44	18.73	3.63%	17	493.27	507.66	14.39	2.92%
5	432.50	443.71	11.21	2.53%	18	381.33	361.13	20.20	5.30%
6	364.97	373.38	8.41	2.25%	19	350.62	362.73	12.11	3.45%
7	458.75	467.94	9.19	1.96%	20	441.83	413.32	28.51	6.45%
8	392.21	412.25	20.04	4.86%	21	334.33	339.92	5.60	1.67%
9	405.62	395.31	10.31	2.61%	22	334.33	339.92	5.60	1.67%
10	451.01	442.22	8.79	1.99%	23	388.49	396.67	8.18	2.11%
11	425.00	424.80	0.20	0.05%	24	394.28	383.04	11.24	2.85%
12	524.30	527.93	3.63	0.69%	25	378.01	364.76	13.25	3.50%
13	394.36	401.28	6.92	1.73%	26	359.69	384.31	24.62	6.85%
			MAE = 2.49 ms		27	427.83	423.62	4.21	0.98%
			MRE = 2.75%		28	415.70	400.88	14.83	3.57%
			R^2 = 0.94		29	408.44	401.19	7.25	1.78%
					30	421.97	425.97	4.00	0.95%
					31	364.35	380.54	16.19	4.44%
					32	358.77	373.43	14.66	4.09%
					33	356.36	374.35	17.99	5.05%
					34	358.77	383.04	24.27	6.76%
					35	356.36	379.31	22.96	6.44%
					36	398.53	388.25	10.28	2.58%
					37	418.30	422.85	4.55	1.09%
								MAE = 14.14 ms	
								MRE = 3.65%	
								R^2 = 0.81	

4.48 mmHg. In the case of the diastolic pressure, the estimation is more accurate, since 13 cases are estimated with an AE between 5 and 10 mmHg. While, for the remaining cases (24 cases) the AE obtained is less than 5 mmHg. Overall, the MAE found in the estimation of SBP is 3.91 mmHg with a STD of 2.58 mmHg. This result is also confirmed by the obtained R^2 which is higher (0.81) in the case of DBP than that of SBP which is 0.67 determined for all 37 subjects.

4.2 Comparison with other works

Table 6 presents a comprehensive comparison between the performance of the proposed method in this paper (using PCG with ANN) and recent similar works in literature, e.g. [7, 8], which uses two signals (PCG and PPG) to estimate BP. The evaluation of this comparing study is carried out using respectively, the MAE, the STD and the Pearson Correlation Coefficient r, where the best results are shown in bold. One should note that the work presented in [8] is limited to SBP estimation only.

As reported in Table 6, the estimation of SBP by the proposed method is more related to the measured value since the MAE±STD is 6.48±4.48mmHg compared to that described in [7, 8] where the respectif MAE ± STD are 7.47 ± 11.08 mmHg and 6.67±7.47mmHg. Furthermore, the r values obtained for estimating SBP for each of the

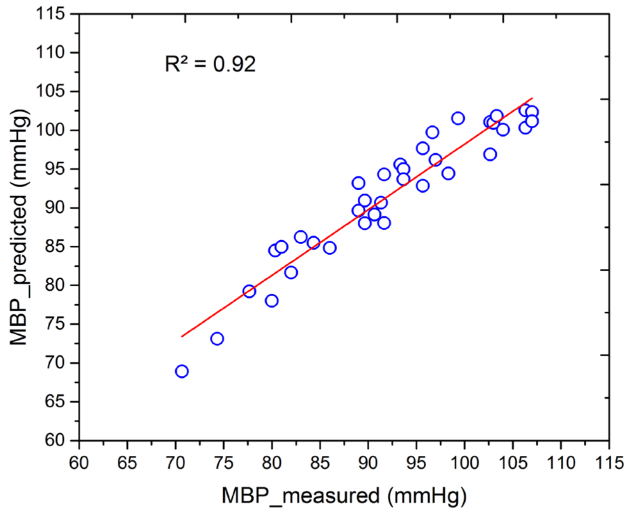


Fig. 9 The correlation between the measured and the predicted values of MBP

evaluated methods are comparable with an r fairly higher in the case of the method proposed in [7], (r = 0.82 for the proposed method and r = 0.84 for the method proposed in [7]).

In the estimation of DBP, the results obtained in the case of the proposed algorithm are comparable to those obtained by the method described in [7]. Indeed, the MAE ± STD are respectively 3.91 ± 2.58mmHg for the former and 3.56 ± 4.53 for the latter. This is also confirmed by the obtained r coefficient where r = 0.89 for the proposed method and r = 0.86 for the method described in [7].

Globally, although the results obtained by the proposed method are highly comparable to those described in the references [7, 8], the proposed method is much more simple (less cumbersome) since it requires only one signal (the PCG signal) to determine blood pressure.

5 Discussion

In this paper, a new approach for estimating blood pressure through PCG signal is described and evaluated. In fact, from 37 recordings of PCG signal, a grouping of two classes is approved in the distribution of the diastolic duration (S12) compared to the pulse transit time (PTT). These classes are best curve fitted by two exponential curves found with a high correlation coefficient given by $R^2 = 0.94$ for class1 and $R^2 = 0.82$ for class2.

To achieve the blood pressure estimation, an algorithm based on neural network is developed to classify all data on the two found classes according to some inputs (sex, height, weight, S12, S21 and HR). According to the result of the ANN, the appropriate correlation equation to estimate PTT then MBP was selected. The SBP and the DBP were then determined through the obtained MBP.

The obtained results show a high accuracy in the estimation of MBP. This was confirmed by the high correlation coefficient $R^2 = 0.91$ obtained by correlating the measured MBPs and the estimated ones. Furthermore, the estimations of the SBP and the DBP are achieved with a good precision since their estimations compared to the measured ones were achieved with respectively MAE ± STD = 6.48 ± 4.48 mmHg and 3.91 ± 2.58 mmHg. These are highly comparable to those recommanded by the AAMI standard which are 5 ± 8 mmHg.

6 Conclusion

In this paper a method is proposed to measure Blood pressure through the PCG signal. The method is based on measuring the diastolic and the systolic durations in the PCG signal. The analysis of this durations show that these durations more particularly the diastolic duration is closely related to PTT and therefore can be used to determine the pressure. However, further research is needed for testing our system in the ambulatory measurement of BP, also, for investigating other parameters for a direct BP estimation through PCG signal. This method has significant potential to advance healthcare since PCG requires minimal low-cost equipment to be recorded and can be easily adapted to smartphones technology.

Table 5 The SBP and DBP estimation results

Subjets	SBP (mmHg)		Absolute error	DBP (mmHg)		Absolute error
	Measured	Predicted		measured	Predicted	
01	107	113.52	6.52	71	70.89	0.11
02	103	112.52	9.52	75	70.25	4.75
03	119	111.25	7.75	61	69.44	8.43
04	101	96.44	4.56	61	59.98	1.02
05	129	122.54	6.46	69	76.64	7.64
06	117	122.07	5.07	85	76.34	8.65
07	101	111.85	10.85	71	69.82	1.18
08	136	132.76	3.24	86	83.17	2.82
09	136	132.76	3.24	86	83.17	2.82
10	118	117.29	0.71	77	73.29	3.70
11	116	125.65	9.65	82	78.63	3.36
12	140	131.02	8.98	75	82.06	7.05
13	132	127.33	4.67	88	79.70	8.29
14	113	117.94	4.94	77	73.71	3.29
15	105	124.01	19.01	85	77.58	7.41
16	127	124.90	2.10	77	78.15	1.15
17	130	119.27	10.73	72	74.56	2.55
18	142	131.50	10.50	85	82.36	2.63
19	141	134.71	6.29	89	84.42	4.58
20	139	134.43	4.57	91	84.23	6.76
21	141	131.80	9.20	89	82.56	6.44
22	139	132.90	6.10	91	83.26	7.74
23	130	133.38	3.38	84	83.56	0.43
24	129	126.42	2.58	81	79.12	1.87
25	102	91.00	11.00	55	56.51	1.50
26	122	102.81	19.19	59	64.05	5.04
27	127	115.86	11.14	74	72.38	1.62
28	105	104.40	0.60	64	65.06	1.05
29	125	115.81	9.19	72	72.35	0.34
30	135	132.60	2.40	87	83.07	3.93
31	112	111.70	0.30	73	69.72	3.27
32	129	124.16	4.84	83	77.68	5.32
33	137	128.38	8.62	75	80.37	5.37
34	115	119.61	4.61	77	74.77	2.23
35	125	123.19	1.81	78	77.06	0.93
36	104	107.56	3.56	71	67.08	3.92
37	132	133.77	1.77	89	83.81	5.18
		MAE = 6.48			**MAE = 3.91**	
		STD = 4.48			**STD = 2.58**	
		R^2 = 0.67			**R^2 = 0.81**	
		r = 0.82			**r = 0.89**	

Table 6 Comparison with other works

Work	Number of subjects	Signals	Index	SBP			DBP		
				MAE	STD	r	MAE	STD	r
This work	37	PCG	S21	**6.48**	**4.48**	0.82	3.91	**2.58**	**0.89**
[7]	24	PCG-PPG	PTT	7.47	11.08	**0.84**	**3.56**	4.53	0.86
[8]	85	PCG-PPG	VTT	6.67	8.47	–	–	–	–

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in these studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the Helsinki declaration and its later amendments or comparable ethical standards. The following ethical issues were honored

Informed consent The participants were informed about the purpose of the study and their participation. The participants were also informed that their participation was voluntary and that they were free to withdraw their participation at any time.

Confidentiality and Anonymity In order to ensure confidentiality and anonymity, the identity ofthe participants was kept anonymous. To this effect, a fictitiousnames were used.

Permission was sought from the department principal to allow the use ofnecessery materials needed for the succes of our experiments.

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