HUMAN BLOOD PRESSURE MEASUREMENT USING MACHINE LEARNING STRATEGY

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A technique based on a machine learning approach is suggested and studied for blood pressure measurements. The proposed technique uses a noninvasive cuffless approach for blood pressure evaluation. In order to extract blood pressure data using this noninvasive cuffless method, pulse wave velocity or pulse wave travel time (PTT) are estimated by both signal processing of electrocardiogram (ECG) and photoplethysmogram (PPG) data records. For study performed by computer simulations, the ECG and PPG records were taken from an open database. Errors arising both for systolic and diastolic arterial pressure evaluation were estimated. Computer simulation results indicate that using machine learning strategy and using only PTT parameters provide a considerable decrease in root mean square errors both for systolic and diastolic human blood pressure data.

KEY WORDS: blood pressure measurement, electrocardiogram, photoplethysmogram, QRS complex, digital signal processing, machine learning, neuron network

1. INTRODUCTION

Hypertension, or high blood pressure (BP), is a worldwide common and dangerous phenomenon affecting more than 35% of the population. This pathology provokes numerous cardiovascular and cerebral-vascular diseases and causes approximately 31% of deaths around the globe. It should be stressed that 85% of these deaths are provoked by heart attack or stroke (http://www.who.int/gho/ncd/risk_factors/en/). Hypertension insensibly destroys different human internal organs like blood vessels, brain, eyes, and kidneys. The majority of hypertensive patients often do not pay attention to their disease, and because of this, hypertension was called a silent killer (WHO, 2013). Recently, hypertension diseases have expanded from older people to the younger population. As a result, large numbers of people need periodic and sometimes continuous BP measurement.

Nowadays, techniques developed for BP measurement can be divided into two classes, direct (invasive) and indirect (noninvasive) techniques. The BP sensor is located just on the arterial vessel for invasive measurements in order to provide high accuracy and regularity of the measurements. However, such an approach is associated with a number of risks. Therefore, direct BP measurements are used only in extreme cases at a hospital and under the care of experienced medical personnel.

Noninvasive BP measurement techniques (Sharma et al., 2017; Ding et al., 2016) are based not on the immediate evaluation of the intravascular BP but on the extraction and analysis of different data contained in cardiac activity and hemodynamics. Note that noninvasive techniques are safer and more convenient in real-life practice. Common noninvasive methods such as oscillometric and auscultatory techniques (Sharma et al., 2017) use controlled artificial barriers introduced for pulse wave (PW) propagation in its way along the vascular bed and measuring the reaction of blood flow to this barrier (Ding et al., 2016).

So-called occlusal (this term comes from Latin word *occlusio*, i.e., locking) usually is used as a barrier that is located on the shoulder, wrist, or finger. External pressure is created at the noted occlusal locations. As a result, the nature of the blood flow changes at the area of blood vessels both under the cuff and below it. Estimation of these variations by some oblique symptoms like the presence, magnitude, and pattern of PW pulsations and comparing them with air pressure in the cuff allows us to determine the parameters of intravascular BP value.

Unfortunately, using the compression cuff for BP measurements causes serious drawbacks for portable devices operating during continuous and long-term BP monitoring. A compression cuff causes the patient some discomfort by continuous pumping of the cuff. Because of this, researchers are searching for an alternative to common cuff-based BP measurement and continuous monitoring techniques.

The relationship of BP with both manifestations of cardiac activity and hemodynamics such as electric, acoustic, and mechanic serves as the basis for development of cuffless BP measurement techniques. In addition, cardiac activity and hemodynamic parameters can be measured and registered by using a noninvasive approach—without any compression cuff—by rather simple technical instrumentation like electrocardiogram, phonocardiogram, photoplethysmogram, rheogram, mechanical pulsogram, and the like.

First attempts dedicated to the development of a cuffless strategy for BP measurement were performed by using BP measurements evaluated in the form of pulse wave velocity (PWV) along the blood vessel or the opposite value evaluated as pulse wave propagation time, or pulse travel time (PTT), between two points located in the vascular system (Ding et al., 2016; Nye, 1964).

The relationship between BP and PWV values was defined long ago; however, first, it was theoretically substantiated by Moens and Korteweg (MK) (Gribbin et al., 1976). Their approach can be explained as follows: PWV value depends on the biomechanical features of blood vessels, for example, elasticity E, wall thickness h, and inner diameter d of blood vessel, as well as blood density ρ. According to the MK approach, the latter values are related by the following equation as

$$PWV = \sqrt{Eh / \rho d}\ . \tag{1}$$

Taking into account Eq. (1), PTT value evaluated along the part of the blood vessel having the length of L can be written as

$$T = PTT = \frac{L}{PWV} = \frac{L}{\sqrt{Eh / \rho d}}\ . \tag{2}$$

The empirical relationship between the vessel elasticity E with flexible wall and the inner pressure P can be written in the following form:

$$E = E_0 e^{\alpha P}, \tag{3}$$

where E_0 is the initial elasticity value, and α is the coefficient depending on the features of the vascular wall. Substituting Eq. (3) into Eq. (2) and performing simple transforms lets us write the expression for the relationships between BP and PTT (Teng and Zhang, 2003) as

$$BP = P = -\frac{2}{\alpha} lnT + \frac{1}{\alpha} ln\left(\frac{L^2 \rho d}{hE_0}\right) \approx -\alpha PTT + b\ . \tag{4}$$

The latter expression indicates that under constant values of the coefficients that define the parameters and vessel state, the variations of BP are approximately inversely proportional to the time of PW propagation. This obstacle led to the first interest in the study of cuffless BP measurements. However, despite the fact that the approach based on the relationships between BP and PTT is hopeful, and a number of publications appeared during the last 15 years in that area (Sharma et al., 2017; Ding et al., 2016; Bramwell and Hill, 1922; Fung et al., 2004; Poon and Zhang, 2005; Jadooei et al., 2013; Kachuee et al., 2017), many problems remain to be solved for large clinical application of this technique. The main problems are providing the calibration and ensuring the accuracy of the measurements. Different approaches using Eq. (4) and various expressions linking BP with PTT are described in Thomas et al. (2016). Researchers indicated in their studies that the root mean square errors (RMSEs) obtained for different expressions are close to each other in value. For this reason we will utilize further the linear equation in the form of $y = ax + b$.

The necessity of calibration to provide the required accuracy in BP measurements is because of the following reasons. First, the values of the physiological parameters contained in Eq. (4) are known approximately, and they can vary from one patient to another, as well as for one specific patient under variation of physical condition and external influences. Second, the MK equation specifies the relationship between BP and PTT only on the basis of hemodynamic laws that exist in elastic vessels. However, the variations of the endothelial layer are not taken into account. In addition, it should be stressed that the cardiovascular system supports automatic regulations swept by multiloop negative feedback (NF). Conditions of this system are defined by NF parameters: the current activity of humeral, sympathetic, and parasympathetic divisions in the cardiovascular system. Hence, an attempt at simplification of the model to the MK equation can be unreliable under conditions when a patient's physiological state differs very much from the supposed state. Third, a linear model of the relationships between BP and PTT used by the majority of researchers (Antonchyk et al., 2016; Yan and Zhang, 2007; Rundo et al., 2018; Zeng-Ding Liu et al., 2018) is valid only within a small range of BP variations. The techniques dedicated to improvement of the calibration problem and using adaptive algorithms (e.g., adaptive Kalman filtering; Zhang et al., 2017) are not able to radically solve this problem.

Due to the limitation of the simplest model based on the MK equation, several alternative models have been proposed. These models are based not only on the relationships between BP and PTT, but also on other compatible activity and hemodynamic parameters like current heart rate (HR), heart rate variability (HRV) parameters, and amplitude and temporal parameters defining the PW shape. Such an approach allows expansion of the model by an additional set of parameters like striking volume, cardiac emission, arterial hardness, and vessel resistance. For instance, myocardium cancellability can be estimated by using the declination of the systolic PW increasing. Cardiac output and general peripheral resistance can be evaluated from the declination of the PW diastolic peak. Parameters of HRV and current HR can be used for measurement of striking volume and minute cardiac output (Poon and Zhang, 2005; Jadooei et al., 2013; Kachuee et al., 2017; Yan and Zhang, 2007; Rundo et al., 2018). However, for the MK model, the linear, logarithmic, opposite, or squared relationship between BP and measured parameters was used. Therefore we can use the observed equation and obtain an expression for evaluation of the calibration coefficients, or for this purpose, use the simplest linear or nonlinear regression techniques (Ding et al., 2016; Jadooei et al., 2013; Kachuee et al., 2017). Complication of the model requires more complicated methods for prognosis modeling. It allows, for example, controlling data processing by machine learning.

The objectives of the paper are the following. First, only one PTT parameter is used for BP computation, which improves the performance of the BP estimation technique with the help of additional parameters in the MK equation. Second, a machine learning technique is used in order to check the possibility of true BP computation without computing the coefficients contained in the MK equation. Third, an examination of the proposed approach by computer simulations performed for real-life biomedical signal records contained in open access database is provided.

2. SUGGESTED STRATEGY FOR CUFFLESS BP MEASUREMNTS

For further study and examination, data were taken from the open access database MIMIC (Johnson et al., 2016). In addition, we also used the signals recorded by the accumulation of single-channel electrocardiogram (ECG) and photoplethysmorgram (PPG) signals in the system we developed (Viunytskyi et al., 2020) using a BP monitor and occlusion cuff. Single-channel ECG and PPG recorders, as well as the CardioSens ECG and BP Holter monitor recorder are demonstrated in Fig. 1. MIMIC data are the sets of signals contained in the ECG recorded on the patient's chest. PPG signals were recorded from the patient's finger; as well, the initial values of the systolic and diastolic BP values were accumulated with time intervals equal to 1 min by using an invasive sensor that was introduced in the patient's shoulder artery. Strategy of the verification experiment is shown in Fig. 2.

FIG. 1: Single-channel ECG and PPG recorder, as well as CardioSens ECG and BP Holter monitoring recorder

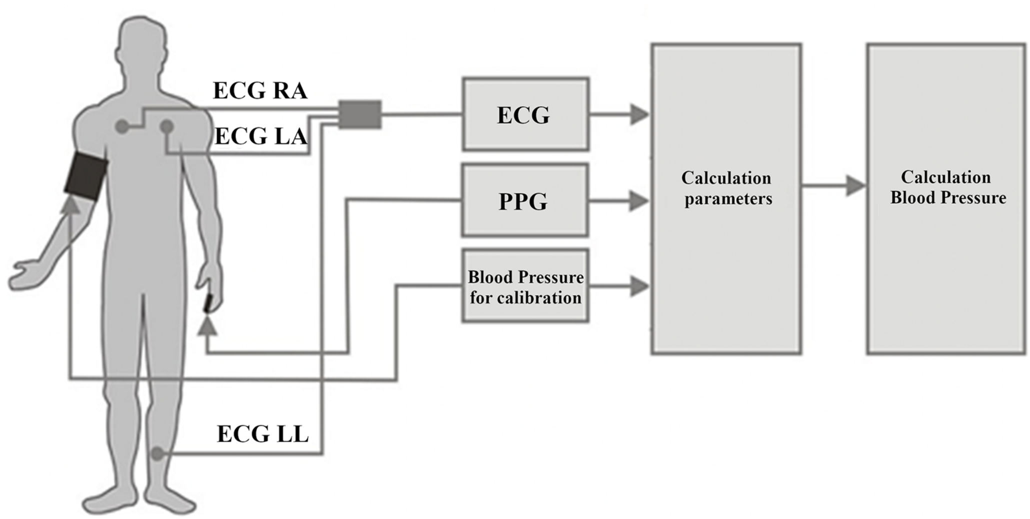

FIG. 2: Blood pressure evaluation

Examples of ECG and PPG records are demonstrated in Fig. 3. QRS complex key locations are marked in Fig. 3; note that QRS complex is detected by exploiting the algorithms described in Viunytskyi et al. (2017). Detection of key points in the PPG signal is demonstrated in Fig. 4.

Figure 4 shows that the key PPGa and PPGc points are detected in the PPG signal as minimum and maximum points relative to the PPGb point, which is detected by the maximum of its derivation. The algorithm described in Viunytskyi et al. (2017) was used for computations.

To evaluate the temporal PTT parameter, it is necessary to transfer from the values represented in the signal samples to the values represented in time domain. The PTT parameter can be computed according to the following expression:

$$PTT_{(a,b,c)} = (PPG_{(a,b,c)} - QRS\ Position)/Fs \quad \left[seconds\right], \tag{5}$$

where *Fs* is the signal sampling frequency; *PPGa,b,c* are the point locations taken in the PPG signal samples; and *QRS Position* is the location of the QRS complex given in the samples.

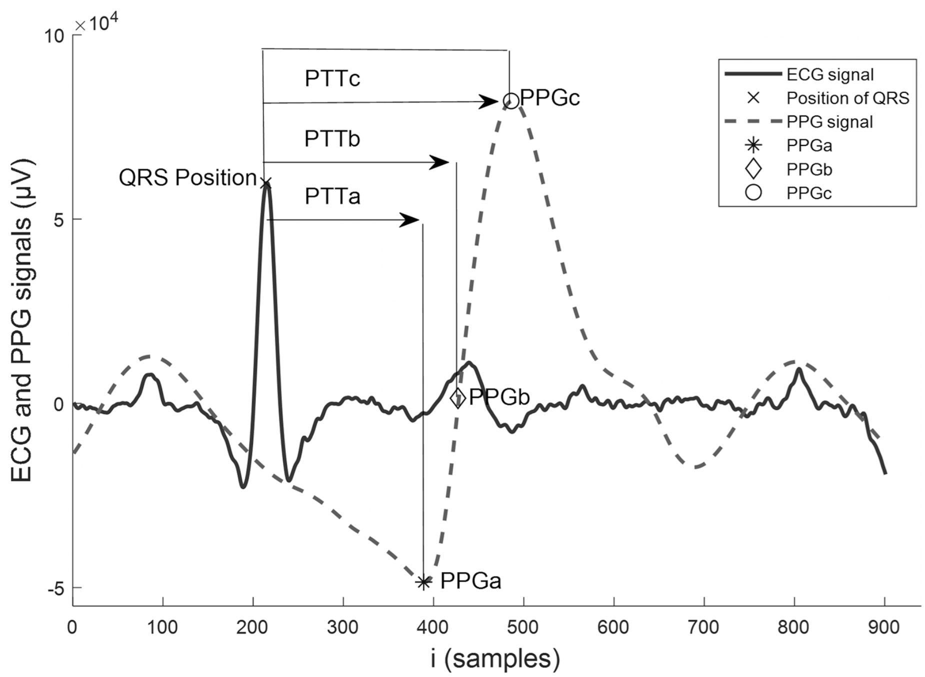

FIG. 3: Examples of ECG and PPG records containing marked points in the PPG signal

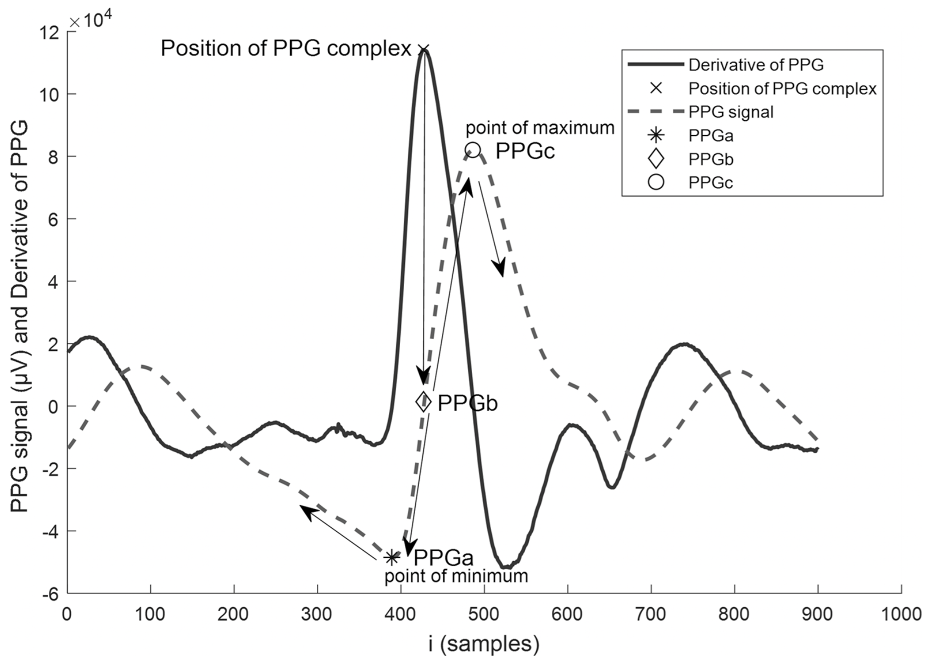

FIG. 4: Detection of the key points on the PPG signal

After performing given signal processing procedures, we obtain the data in a matrix form, which introduces three PTT values measured from one heart contraction to another. Since BP measurements are executed once per minute, point detection and parameter computations performed from one heart contraction to another can vary per minute. Therefore, averaging PTT parameters during a 1 min interval is carried out.

After that, evaluation of the PTT parameter is performed in the next signal part of 1 min duration. The latter procedure is repeated until the end of the record. In the considered case, the records were of 8 hr duration on average. Because of this, 1344 PTTa, b, c values were obtained at the output as follows: 448 values for each case of evaluation of the PTT parameter and 448 reference values for systolic and diastolic arterial BP for a single patient. Correlation coefficients between PPTa, b, c and initial arterial pressure values computed for 31 patients are represented in Table 1.

Table 1 shows that the correlation coefficient values are larger for systolic BP compared to the correlation coefficients computed for diastolic BP. Since in this section we pay most attention to the PTT parameters, it is necessary to select it for maximum correlation relative to BP values. Because of this, in further computational simulations we will use the PTTc parameter as the PTT parameter.

By solving the following simple equation in the form of $y = ax + b$ (4), the coefficients a and b were determined, and Eqs. (6) and (7) were written for the systolic and diastolic pressure estimations as

$$Systolic\ BP\ =\ 259.605\ -\ 0.6459 \cdot PTT\ , \tag{6}$$

$$Diastolic\ BP\ =\ 259.122\ -\ 1.1175 \cdot PTT\ . \tag{7}$$

Results of BP computations for one patient by using Eqs. (6) and (7) and using only one PTT parameter are shown in Fig. 5. Detection of the data is performed by 1 min time intervals during the total signal record time of 520 minutes; that is, one value of arterial pressure per 1 min in a time interval of 520 min.

Note that different equations were obtained for different people since the relationships between PTT parameter and BP value are of individual forms for people. It also influenced the correlation coefficients in Table 1 since for one group, a direct relationship is observed when the correlation coefficient is positive. In the opposite

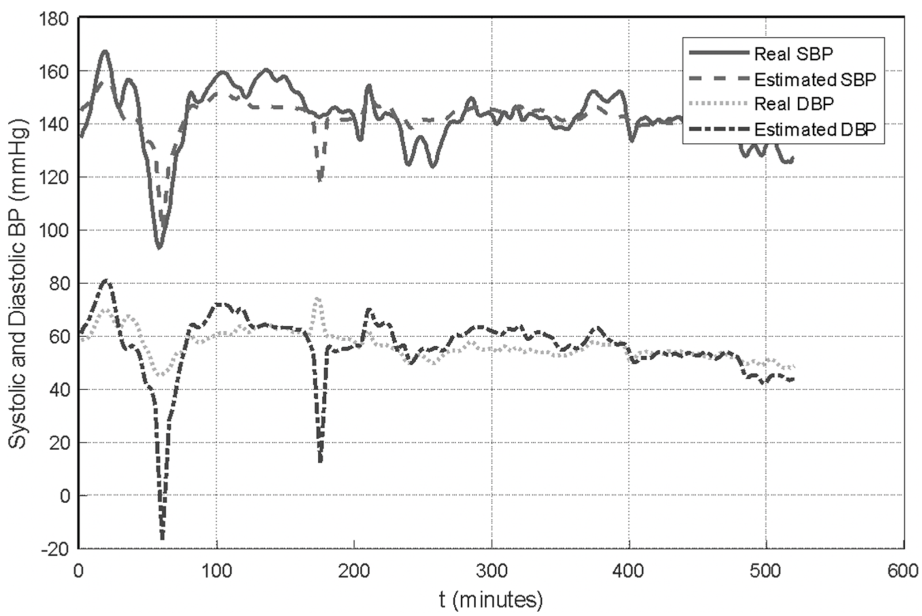

FIG. 5: Results of BP computation by using PTT parameter

TABLE 1: Correlation coefficients evaluated for the PTT parameters relative initial BP values

Parameter	Correlation coefficients relative systolic BP values	Correlation coefficients relative diastolic BP values
PTTa	0.3869	0.066
PTTb	0.3189	0.099
PTTc	0.3473	0.168

case, correlation coefficients are negative. As a result of averaging, the coefficients tend toward small values. However, results of systolic BP computation are of reasonable values as can be seen from Fig. 5. Errors obtained for systolic pressure evaluation are demonstrated in Fig. 6, and errors obtained for diastolic pressure evaluation are shown in Fig. 7. Mean deviations and RMSE values are also represented in the latter figures.

Figures 6 and 7 show that the mean deviation of evaluated systolic pressure values relative to real systolic pressure values equals –0.39 mmHg and for diastolic pressure equals 0.04 mmHg. RMSE values evaluated for systolic and diastolic pressure are equal to $\sigma^2 = 7.19$ mmHg and $\sigma^2 = 9.84$, respectively. Mean squared deviations are equal to $\sigma = 2.68$ mmHg and $\sigma = 3.13$ mmHg for systolic and diastolic pressures, respectively. Equations (6) and (7) are individual for each separate patient because physiological parameters are known only approximately and they can vary with time. However, there are cases when the regression coefficients in Eqs. (6) and (7) are approximately the same. In such cases, there is an opportunity to determine BP by the expression without changing any coefficients. A serious problem with this approach is the need to correct coefficients that need real BP values. The latter peculiarities significantly complicate and provoke practically impossible use of this strategy at home or in personal mobile devices because the user must perform the correction of the coefficients. The second problem is connected with the personality feature of the given approach since Eqs. (6) and (7) can be used only for one individual patient.

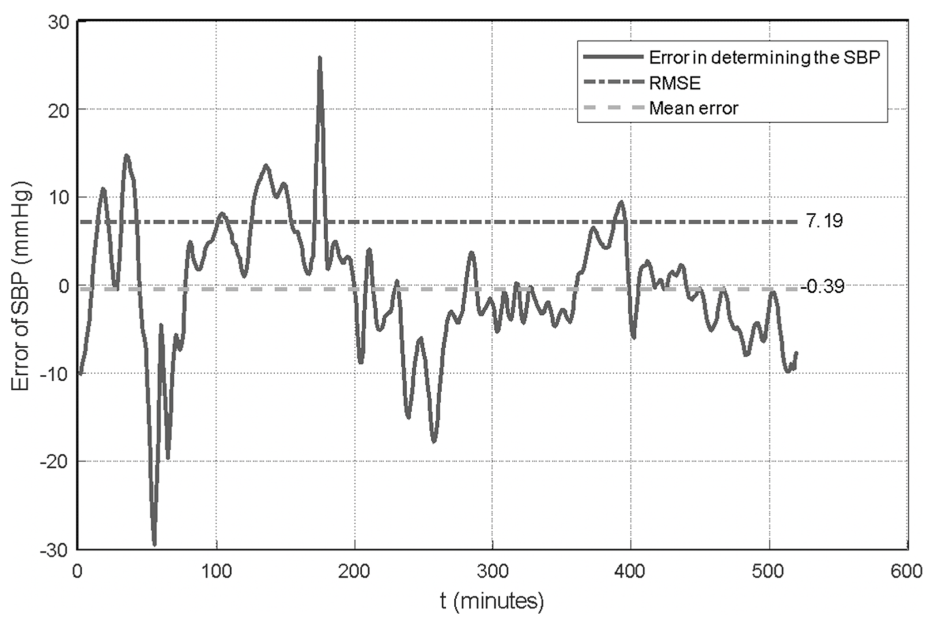

FIG. 6: Errors arising for evaluation of systolic arterial pressure

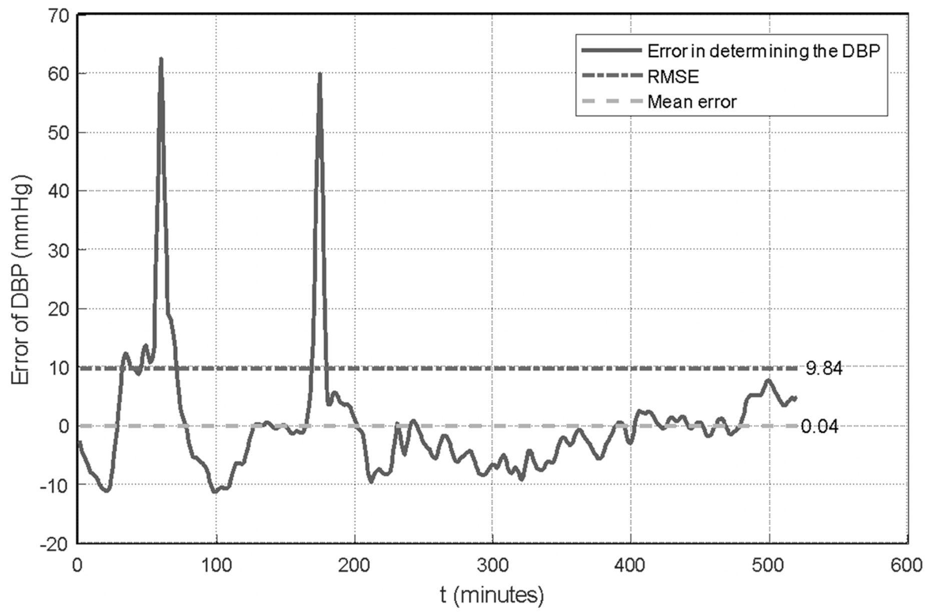

FIG. 7: Errors arising for evaluation of diastolic arterial pressure

For 31 patients, on average, the mean deviation in the obtained systolic pressure value and diastolic pressure value relatively correspond to real values equal to 0.25 mmHg and 0.33 mmHg, respectively. At the same time, RMSE for the systolic pressure and diastolic pressure values are equal to $\sigma^2 = 5.71$ mmHg and $\sigma^2 = 6.13$ mmHg, respectively. Mean squared deviation values evaluated for the systolic pressure and diastolic pressure values are equal to $\sigma = 2.38$ mmHg and $\sigma = 2.47$ mmHg, respectively.

3. COMPUTATIONS BY USING EXPANDED SET OF PARAMETERS

An example of detecting the additional key points on the PPG signal by derivative is demonstrated in Fig. 8. As in the abovementioned case, detection of minimum and maximum points within the PPG signal part is performed just for the detected point. The points for which the process was not illustrated in Fig. 8 are also detected by seeking minimums and maximums in the PPG signal but not by its derivative.

The final version of the key points detection on the ECG and PPG signals, marked correspondingly, is demonstrated in Fig. 9.

The following parameters used for BP computations are represented below:

$$P1 = (PPG_a - QRS\ Position)/Fs\,, \tag{8}$$

$$P2 = (PPG_b - QRS\ Position)/Fs\,, \tag{9}$$

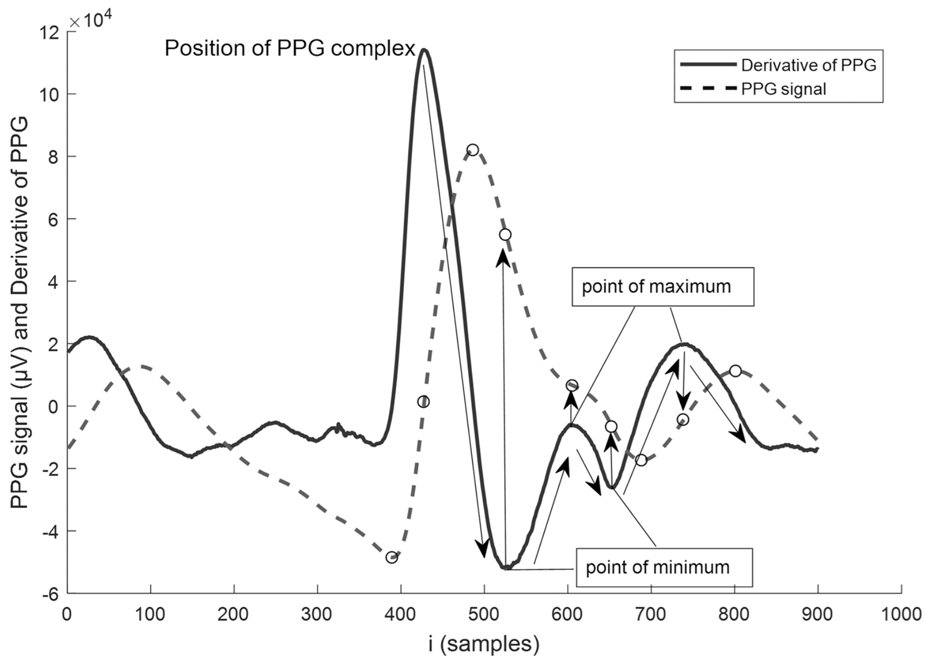

FIG. 8: Detection of the additional points on the PPG signal

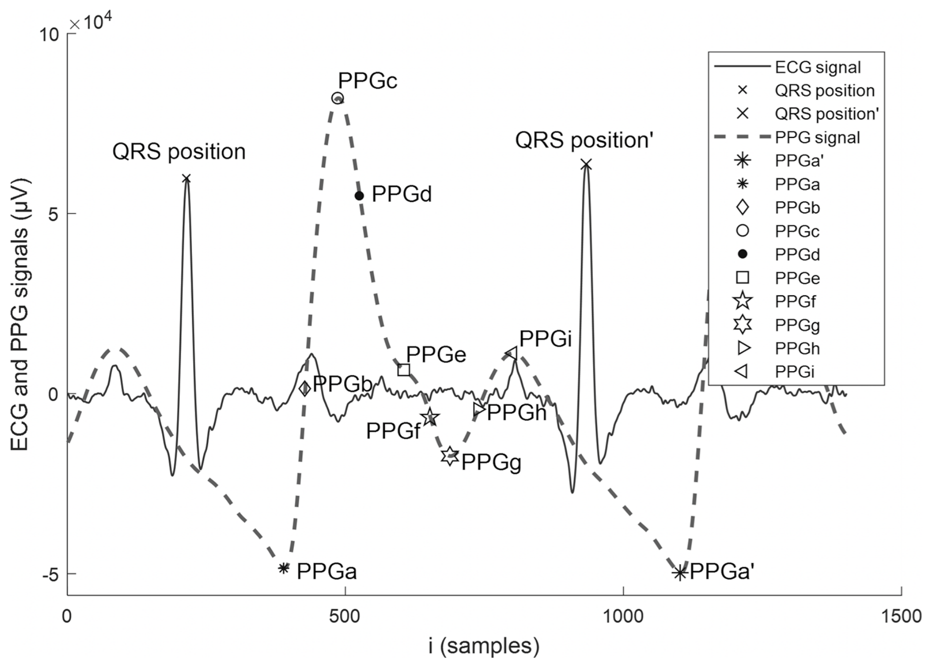

FIG. 9: Detection and marking of the additional points on the PPG signal

$$P3 = (PPG_c - QRS\ Position)/Fs, \tag{10}$$

$$P4 = (PPG_i - QRS\ Position)/Fs, \tag{11}$$

$$P5 = (PPG_g - PPG_d)/(PPG_d - PPG_c), \tag{12}$$

$$P6 = (PPG_i - PPG_a)/(PPG_{a'} - PPG_a), \tag{13}$$

$$P7 = (PPG_d - QRS\ Position)/Fs. \tag{14}$$

By solving the equation system, Eq. (4) was obtained for evaluation of both systolic and diastolic BP with an expanded set of parameters as follows:

$$\begin{aligned} Systolic\ BP = 260 - 0.198 \cdot P1 - 0.108 \cdot P2 - \\ -0.08 \cdot P3 - 0.037 \cdot P4 - 30.71 \cdot P5 - 35.31 \cdot P6 \end{aligned}, \tag{15}$$

$$\begin{aligned} Diastolic\ BP = 260 - 0.167 \cdot P3 - 0.133 \cdot P7 - \\ -0.08 \cdot P4 - 63.75 \cdot P5 - 73.48 \cdot P6 \end{aligned}. \tag{16}$$

As in the case of using only one PTT parameter, these equations are valid only for one individual patient. Computation results obtained for systolic [Eq. (15)] and diastolic [Eq. (16)] BPs are shown in Fig. 10. Errors arising from evaluation of systolic and diastolic BPs are demonstrated in Figs. 11 and 12, respectively.

It can be seen from the obtained results that additional parameters did not improve computation performance of systolic BP, but the computation quality of diastolic pressure was improved by approximately two times. Comparative data are represented in Table 2.

Averaged data accumulated from 31 patients are equal to the following values: mean errors arising for systolic and diastolic BP are 0.25 mmHg and 0.31 mmHg, respectively; RMSE for systolic and diastolic pressure are 5.32 mmHg and 3.7 mmHg, respec-

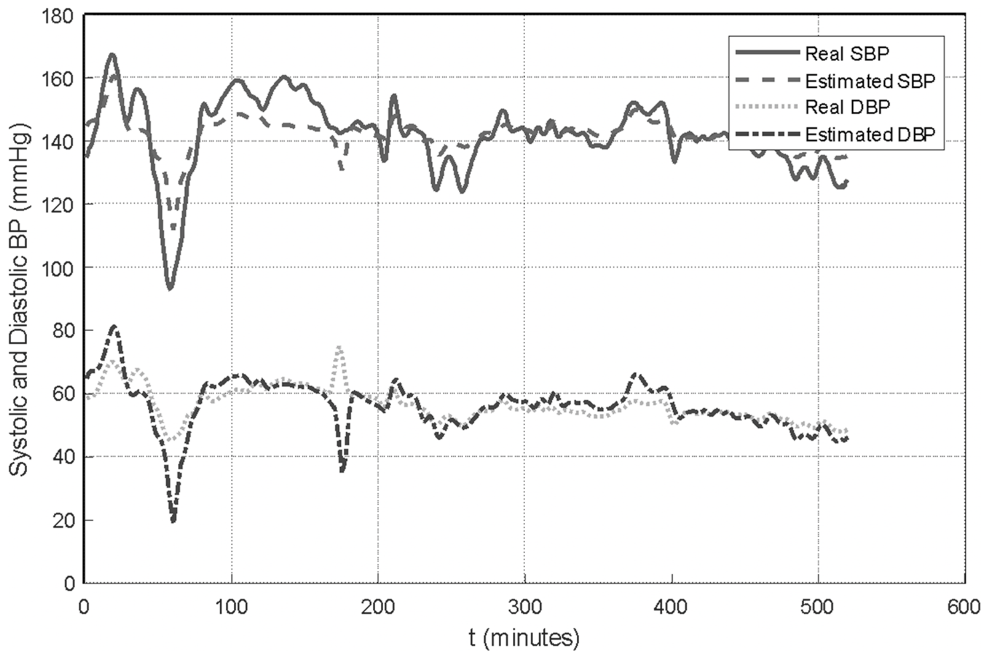

FIG. 10: Computation of BP by using additional parameters

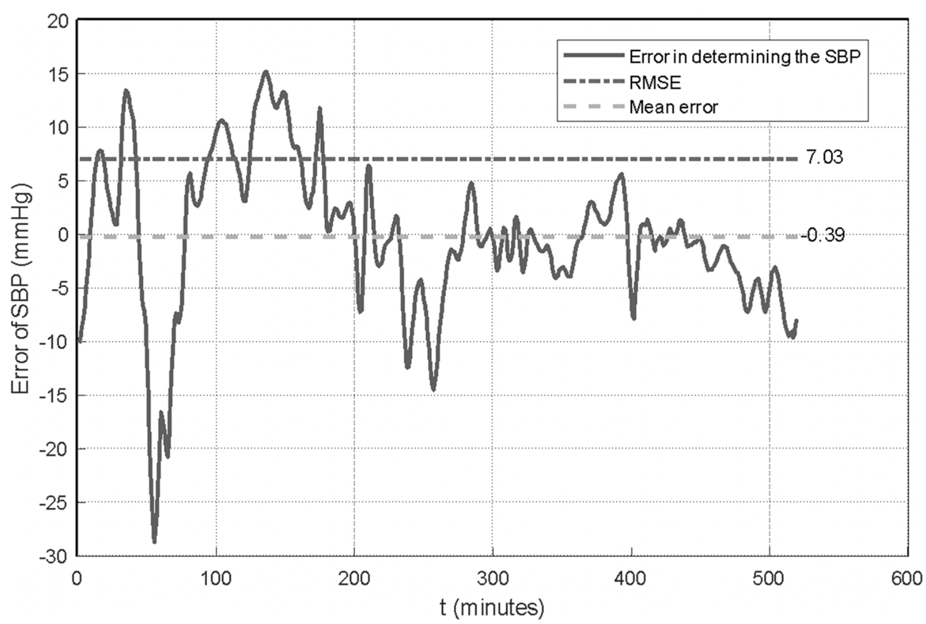

FIG. 11: Error arising for evaluation of systolic pressure

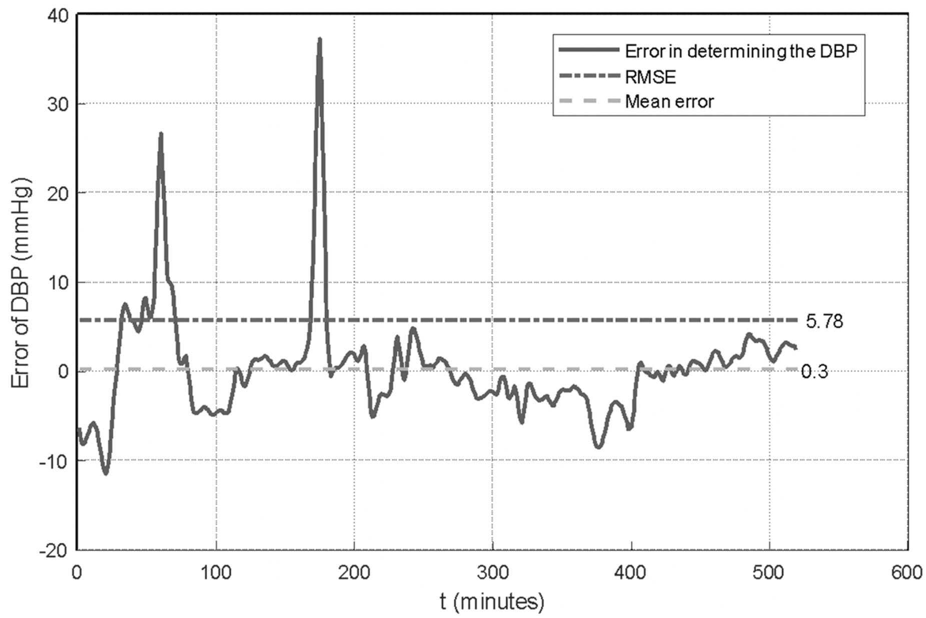

FIG. 12: Error arising for evaluation of diastolic pressure

TABLE 2: Comparison the BP values computed both by Eqs. (5) and (6) and by Eqs. (15) and (16)

Parameter (mmHg)	Systolic pressure (was)	Systolic pressure (became)	Diastolic pressure (was)	Diastolic pressure (became)
Mean error	–0.39	–0.39	0.04	0.3
σ^2	7.19	7.03	9.84	5.78
σ	2.68	2.65	3.13	2.4

tively; mean squared deviation σ for systolic and diastolic pressure are 2.31 mmHg and 1.92 mmHg, respectively.

4. EVALUATION OF BP USING MACHINE LEARNING STRATEGY

More recently, machine learning methods have been proposed to estimate central pressure from various physiological signals such as PPG (Magbool et al., 2021a,b; Srinivasa and Pandian, 2022). Research results indicate that the use of more complicated methods for determining BP gives more stable estimates than when using simple regression equations.

The suggested approach is based on the machine learning strategy. First, recording the set of some physiological signals related to arterial pressure is performed. At the same time, measurement of arterial pressure is executed. Second, surrogate cardiovascular indexes or features are extracted. Model machine learning is executed by using these features or a learning sample. Third, prediction of the BP is carried out using the learned model and a new set of physiological signals. Two different neuron networks were formed for systolic and diastolic pressure evaluation since dependence of PTT parameters on pressure value differs. Structure of the neuron network can be described in the form of the totally related network with six inputs for systolic pressure and five inputs for diastolic pressure, as well as three hidden layers containing 256 neurons in each layer and one input. Parameters for machine learning were used in the form of the same values used in the computation with an expanded set of parameters [Eqs. (8)–(14)]. A database of 20 people was created; one half of the data was used for learning and the second half was used both for testing and recording for 11 people. The latter data were utilized only for examination of the neuron network system. It should be also stressed that in our study, people aged 21 to 34 years who did not have problems with their cardiovascular systems participated. Results of computations of systolic and diastolic BP obtained for the patient represented in the previous sections are demonstrated in Fig. 13.

Errors arising for systolic and diastolic BP evaluation are demonstrated in Figs. 14 and 15, respectively. Mean squared deviation values are also shown in the figures.

Figures 14 and 15 show that using a machine learning strategy improves the performance of arterial pressure evaluation. Averaged values accumulated for 31 patients show that mean errors for systolic and diastolic pressures are 0.055 mmHg and –0.014 mmHg, respectively. Variances for systolic and diastolic pressures are 3.59 mmHg and 2.92 mmHg, respectively. Mean squared deviations σ for systolic and diastolic pressures are 1.37 mmHg and –1.7 mmHg, respectively. Note that these results are evidently better as compared with previous results.

Systolic and diastolic pressure values evaluated at the same time for three different people are demonstrated in Fig. 16. It is seen from the curves in Fig. 16 that one neuron

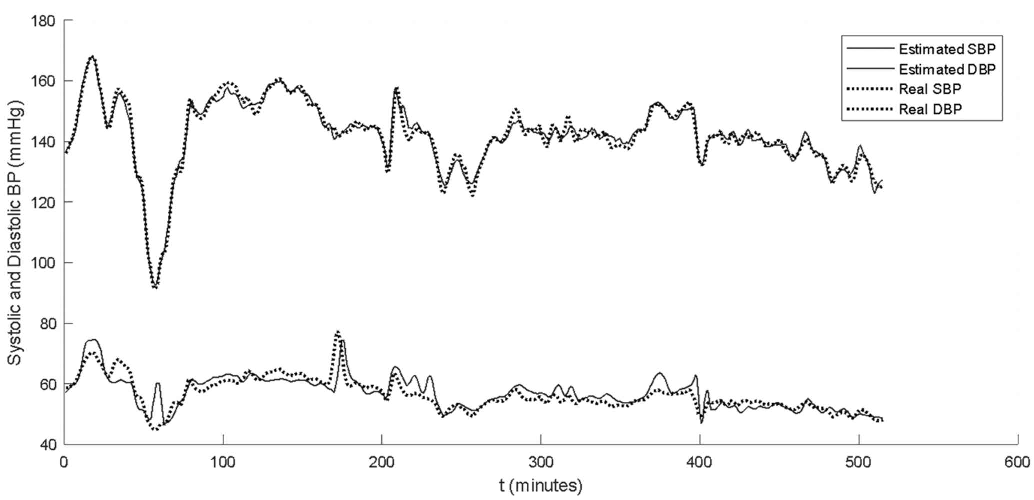

FIG. 13: Evaluation of systolic and diastolic pressure using machine learning strategy

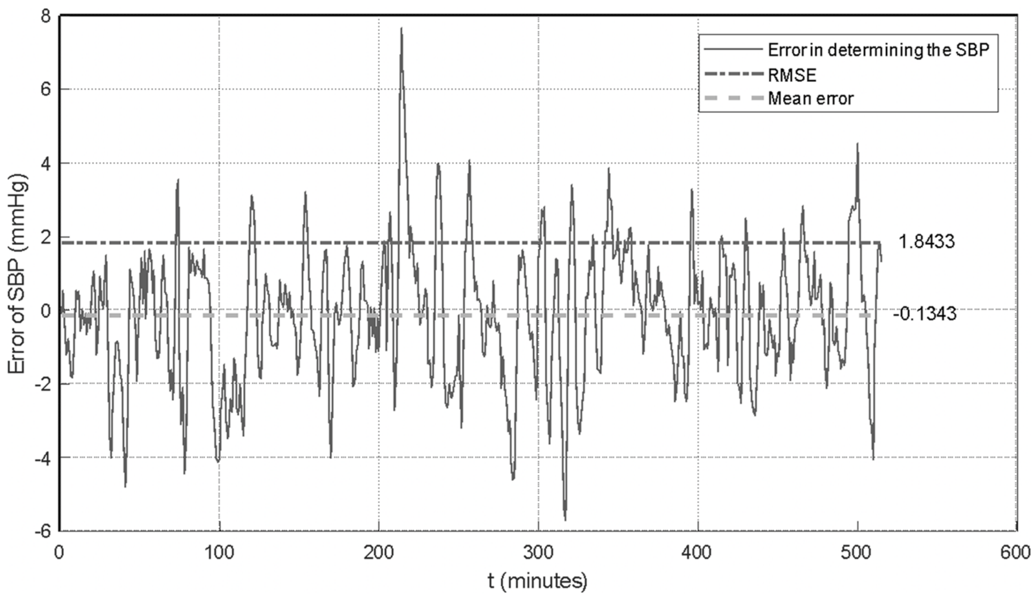

FIG. 14: Error arising for systolic pressure evaluation

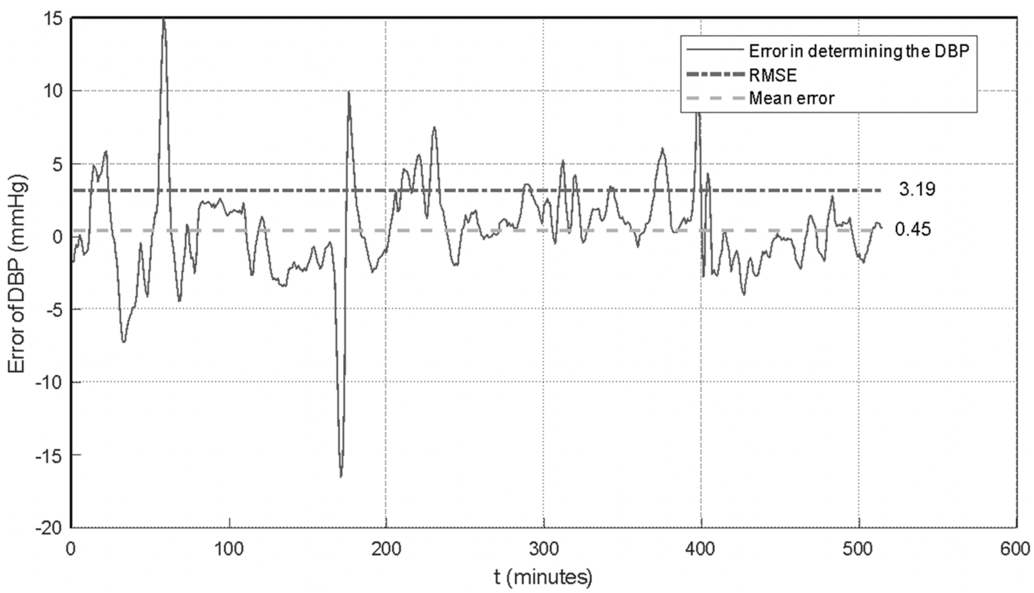

FIG. 15: Error arising for diastolic pressure evaluation

network is able to operate for several people. In order to improve operating performance, additional parameters can be introduced and more people can be involved in the learning sample.

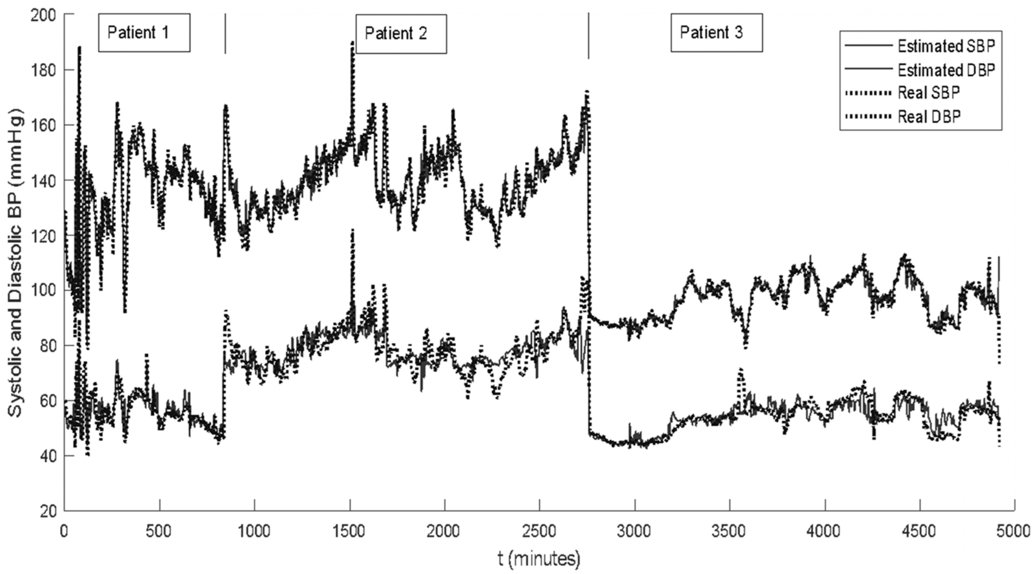

FIG. 16: Systolic and diastolic pressures evaluated at the same time for three different people and for two neuron networks: first, evaluated for systolic and, second, for diastolic arterial pressures

5. DISCUSSION OF OBTAINED RESULTS

As noted above, Eq. (4) is an individual form for different patients. Therefore, it is necessary to recompute the coefficients for each patient. First, researchers tried developing mathematical models in order to find simpler and easier new coefficients in Eq. (4) for new patients by using reference arterial pressure values during 1 min intervals (Yan et al., 2019; Park et al., 2019). It was also shown in Park et al. (2019) that one opportunity exists to determine the given data using only one reference value. However, this result does not allow for the possibility to use the given technique without any calibration procedure. The majority of known results satisfy IEEE requirements for BP measurements executed by the developed techniques. In this paper, obtained results also satisfy the noted requirements since 85% of BP values have deviations relative to reference values within the limits of ± 5 mmHg. This paper also touched on a proposed machine learning technique. However, in this paper, results are represented for people with no cardiovascular pathologies that are connected to BP. They were of the same age and same weight and can demonstrate that the model [Eq. (4)] has coefficients approximately equal to the same values. Because of this, the use of the given neuron network for seeking BP values for other patients, especially for the patients with some pathologies, cannot demonstrate similar results. In the first place, it will be caused by elastic parameters of the vessels as well as vessel length. It can be explained as follows: the longer the vessel length, the greater distance blood flow travels, so the greater time (PTT value) the propagation of pulse wave will take. Even though patients have the same BP values at a fixed moment, the PTT parameters will differ from each other. Taller people will have longer arms, therefore, blood flow takes more time to travel from the heart to the finger where the PPG signal is recorded. So, with the same BP values but with different heights, PTT parameters will be of different values. Because of this, it seems to be reasonable passing from the given parameter only to the parameters contained within the PPG signal. The latter parameters were described in the third section. It has been demonstrated that by using the given parameters, the accuracy of BP evaluation increased and correlation between PTT parameter and BP is of rather low value, as demonstrated by Table 1. Therefore, it seems appropriate to develop and study a model using only PPG signal parameters without using ECG signals and without evaluation of the PTT parameter. Such an approach will be demonstrated in our future studies. Since dependence on the temporal parameters exists within the PPG signal, the probability of the dependence on the spectral components also can exist. Therefore, it will be helpful to further study a strategy of BP computations based on the higher-order spectra called bispectra (Totsky et al., 2015). This strategy can improve the quality of BP measurements. At last, using a larger sample volume is necessary for learning the neuron network operating with different people and different rates, which also can perform BP measurement and its computation for a larger number of patients participating in the primary learning sample. Results of investigations will be presented in our future papers.

6. CONCLUSIONS

Thirty-one records of biomedical signals taken from an open access database were examined in our study. Half of the data contained in 20 records was used for seeking regression coefficients and learning the neuron network and the other half of each record was used for testing. The remaining 11 records were used only for neuron network testing and regression equation examinations.

Results of investigations indicate that by exploiting only the PTT parameter, it is possible to reach average RMSE values equal to 5.71 mmHg and 6.13 mmHg for systolic and diastolic BP, respectively. By using an extended set of parameters, RMSE was not changed and was equal to 5.32 mmHg and 3.7 mmHg for systolic and diastolic pressure, respectively. Note that the obtained improvement for diastolic pressure is 1.66 times. By using machine learning and the models based on the neuron networks, RMSEs are equal to 3.59 mmHg and 2.92 mmHg for systolic and diastolic BP, respectively.

It should also be noted that the use of neural networks in the problem of determining BP without a cuff and noninvasive strategy makes it possible to develop a method that will simultaneously determine BP in several patients. In turn, standard methods based on regression equations can be used only on the one patient for whom they were calculated. The more patients who will participate in training the neural network, the more resistant it will be to other patients. However, this statement remains to be verified in future investigations. Also in our future studies, we plan to introduce tools that will improve the method for its resistance to HR. Why does such a need arise? Because depending on the HR, the duration of one peak of the PPG signal changes (see Fig. 9, demonstrating the duration in time between the points PPGa and PPGb). It also leads to a difference in some computed parameters. With the same BP but different HRs, the parameters will vary from one patient to another. In addition, these parameters will vary due to the parameters of the vessels, such as wall thickness and elasticity. These parameters were indicated in Eqs. (3) and (4), however, we neglected them, assuming that the changes are insignificant. This may also be an erroneous conclusion. Therefore, in future investigations, we plan to place two sensors on one arm of the patient at once to read the PPG signal at a predetermined distance, for example, 1 cm. Between two recorded signals, we plan to find the speed of propagation of the pulse wave, taking into account the points of maxima of two signals (see PPGc in Fig. 9). This will avoid two unresolved problems: (1) for different patients with different heights and different arm lengths, the distance from the sensor on the heart and the sensor on the arm will change, thereby changing the propagation time of the pulse wave from which the regression equations cannot be used for different patients; and (2) in such a short section of pulse wave propagation, it is possible that the parameters of the vessels and their elasticity will indeed not affect anything and they can be ignored, assuming that they are approximately the same for all. Thus, it will be possible to move away from most of the problems and eliminate them, and neural networks and machine learning methods, as in the results of this work, will further improve the results of BP measurements.

REFERENCES

Antonchyk, O., Nasedkin, K., and Sharonov, V., Arterial Blood Pressure Evaluation Based on Joint Processing of the Vital Signs Parameters, *Telecommun. Radio Eng.*, vol. **75**, no. 18, pp. 1679–1693, 2016.

Bramwell, J.C. and Hill, A.V., The Velocity of the Pulse Wave in Man, *Proc. of the Royal Society*, London, no. B93, pp. 298–306, 1922.

Ding, X., Zhao, N., Yang, G.Z., Pettigrew, R.I., Lo, B., Miao, F., Li, Y., Liu, J., and Zhang, Y.T., Continuous Blood Pressure Measurement from Invasive to Unobtrusive: Celebration of 200th Birth Anniversary of Carl Ludwig, *IEEE J. Biomed. Health Inform.*, vol. **20**, no. 6, pp. 1455–1465, 2016.

Fung, P., Dumont, G., Ries, C., Mott, C., and Ansermino, M., Continuous Noninvasive Blood Pressure Measurement by Pulse Transit Time, *Proc. of Engineering in Medicine and Biology Society, IEMBS'04, 26th Annual Int. Conf. of the IEEE*, pp. 738–741, 2004.

Gribbin, B., Steptoe, A., and Sleight, P., Pulse Wave Velocity as a Measure of Blood Pressure Change, *Psychophysiology*, vol. **13**, pp. 86–90, 1976.

Jadooei, A., Zaderykhin, O., and Shulgin, V.I., Adaptive Algorithm for Continuous Monitoring of Blood Pressure Using a Pulse Transit Time, *Proc. of Electronics and Nanotechnology (ELNANO), IEEE XXXIII International Scientific Conference*, pp. 297–301, 2013.

Johnson, A.E.W., Pollard, T.J., Shen, L., Lehman, L., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L.A., and Mark, R.G., MIMIC-III, a Freely Accessible Critical Care Database, *Sci. Data*, 2016.

Kachuee, M., Kiani, M.M., Mohammadzade, H., and Shabany, M., Cuffless Blood Pressure Estimation Algorithms for Continuous Health-Care Monitoring, *Proc. of IEEE Transactions on Biomedical Engineering*, vol. **64**, no. 4, pp. 859–869, 2017.

Liu, Z.D., Liu, J.K., Wen, B., He, Q.Y., Li, Y., and Miao, F., Cuffless Blood Pressure Estimation Using Pressure Pulse Wave Signals, *Sensors*, vol. **18**, no. 12, pp. 4227–4242, 2018.

Magbool, A., Bahloul, M.A., Ballal, T., Al-Naffouri, T.Y., and Laleg-Kirati, T.M., Combining Machine Learning and Blind Estimation for Central Aortic Blood Pressure Reconstruction, *Proc. of 2021 43rd Annual Int. Conf. of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pp. 5512–5517, 2021a.

Magbool, A., Bahloul, M.A., Ballal, T., Al-Naffouri, T.Y., and Laleg-Kirati, T.M., Aortic Blood Pressure Estimation: A Hybrid Machine-Learning and Cross-Relation Approach, *Biomed. Signal Proc. Control*, vol. **68**, pp. 1–18, 2021b.

Nye, E., The Effect of Blood Pressure Alteration on the Pulse Wave Velocity, *Br. Heart J.*, vol. **26**, pp. 261–265, 1964.

Park, J., Yang, S., Sohn, J., Lee, J., Lee, S., Ku, Y., and Kim, H.C., Cuffless and Continuous Blood Pressure Monitoring Using a Single Chest-Worn Device, *IEEE Access*, vol. **7**, pp. 135231–135246, 2019.

Poon, C.C.Y. and Zhang, Y.T., Cuff-less and Noninvasive Measurements of Arterial Blood Pressure by Pulse Transit Time, *Proc. of Engineering in Medicine and Biology Society, IEEE-EMBS'2005, 27th Annual Int. Conf. of the IEEE*, pp. 5877–5880, 2005.

Rundo, F., Ortis, A., Battiato, S., and Conoci, S., Advanced Bio-Inspired System for Noninvasive Cuff-Less Blood Pressure Estimation from Physiological Signal Analysis, *Computation*, vol. **6**, no. 3, pp. 46–63, 2018.

Sharma, M., Barbosa, K., Ho, V., Griggs, D., Ghirmai, T., Krishnan, S.K., Hsiai, T., Chiao, J.-C., and Cao, H., Cuff-Less and Continuous Blood Pressure Monitoring: A Methodological Review, *Technologies*, vol. **5**, no. 2, pp. 21–43, 2017.

Srinivasa, M.G. and Pandian, P.S., Cuff-Less Non-Invasive Blood Pressure Measurement Using Various Machine Learning Regression Techniques and Analysis, *Int. J. Biomed. Clin. Eng.*, vol. **11**, no. 1, pp. 1–19, 2022.

Teng, X.F. and Zhang Y.T., Continuous and Noninvasive Estimation of Arterial Blood Pressure Using a Photoplethysmographic Approach, *Engineering in Medicine and Biology Society, Proc. of the 25th Annual Int. Conf. of the IEEE*, pp. 3153–3156, 2003.

Thomas, S.S., Nathan, V., Zong, C., Soundarapandian, K., Shi, X., and Jafari, R., BioWatch: A Noninvasive Wrist-Based Blood Pressure Monitor That Incorporates Training Techniques for Posture and Subject Variability, *IEEE J. Biomed. Health Inform.*, vol. **20**, no. 5, pp. 1291–1300, 2016.

Totsky, A.V., Zelensky, A.A., and Kravchenko, V.F., *Bispectral Methods of Signal Processing*, Berlin/Munich/Boston: Walter de Gruyter GmbH, p. 199, 2015.

Viunytskyi, O., Shulgin, V., Totsky, A., and Sharonov, V., Non-Invasive Cuff-Less Measurement of Blood Pressure Based on Machine Learning, *Proc. of IEEE 15th Int. Conf. on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering*, Lviv-Slavske, Ukraine, pp. 203–206, 2020.

Viunytskyi, O. and Shulgin, V., Signal Processing Techniques for Fetal Electrocardiogram Extraction and Analysis, *Proc. of IEEE 37th Int. Conf. on Electronics and Nanotechnology,* Kiev, Ukraine, pp. 325–328, 2017.

World Health Organization (WHO), A Global Brief on Hypertension, Silent Killer, Global Public Health Crisis, World Health Day 2013, from https://www.who.int/publications/i/item/a-global-brief-on-hypertension-silent-killer-global-public-health-crisis-world-health-day-2013, 2013.

World Health Organization (WHO), Raised Blood Pressure, from http://www.who.int/gho/ncd/risk_factors/en/.

Yan, C., Li, Z., Zhao, W., Hu, J., Jia, D., Wang, H., and You, T., Novel Deep Convolutional Neural Network for Cuff-less Blood Pressure Measurement Using ECG and PPG Signals, *Proc. of 41st Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Berlin, Germany, pp. 1917–1920, 2019.

Yan, Y.S. and Zhang, Y.T., A Novel Calibration Method for Noninvasive Blood Pressure Measurement Using Pulse Transit Time, *Proc. of the 4th IEEE/EMBS Int. Summer School and Symposium on Medical Devices and Biosensors*, pp. 22–24, 2007.

Zhang, Q., Chen, X., Zhen, F., and Xia, S., Cuff-Less Blood Pressure Measurement Using Pulse Arrival Time and Kalman Filter, *J. Micromech. Microeng.*, vol. **27**, no. 2, 2017.