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Noninvasive Arterial Blood Pressure Estimation using ABPNet and VITAL-ECG

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***Abstract*— Arterial Blood Pressure (ABP) is an important physiological parameter that should be properly monitored for the purposes of prevention and detection of cardiovascular diseases, which represent one of the leading causes of death in the world. Currently, the most common adopted noninvasive blood pressure measurement system is sphygmomanometer, which works by inflating and deflating a cuff around the arm. This work presents ABPNet, a new prediction technique, based on a multilayer perceptron (MLP), which uses ECG and PPG to estimate both systolic and diastolic blood pressure. To train the neural network, signals are gathered from the Physionet MIMIC database. The proposed architecture performances are evaluated w.r.t. both the invasive blood pressure signal and the noninvasive sphygmomanometer measurements. The experimental results are quite promising; they are compliant with the ANSI/AAMI/ ISO 81060- 2:2013 for sphygmomanometer certification because the network predicted values are within +/- 5 mmHg w.r.t. real invasive measurements, as imposed by the legislation. Finally, it is shown how ABPNet can be used to improve the VITAL-ECG, a wearable device designed to acquire vital parameters, such as electrocardiographic (ECG) and photoplethysmographic (PLETH/PPG) signals; indeed, by embedding the ABPNet neural network, VITAL-ECG can be upgraded to estimate, also, ABP. As a consequence, the device could be used to fight cardiovascular diseases and prevent their dangerous effects.**

Keywords—arterial blood pressure, ECG, electrocardiogram, machine learning, neural networks, photoplethysmogram, PPG, VITAL-ECG.

I. INTRODUCTION

Cardiovascular diseases (CVD) represent one of the leading causes of death in the world. Deaths due to cardiovascular diseases reach 17.65 million people per year and 10.46 million people per year die from high blood pressure (BP), which is a section of medical problems that affects the circulatory system [1]. Several studies have demonstrated that arterial blood pressure (ABP), has a close relation with cardiovascular disease. The strong relationship is consistent among different ethnic, gender and age groups [2]. According to the American Stroke Association, the risk of developing cardiovascular disease can be estimated by evaluating the systolic and diastolic pressures [3]. The most dangerous pressure stage is referred to ABP values greater than 180/120 mmHg (hypertensive crisis).

There are two ways to measure blood pressure: direct and indirect. The former is the gold standard and consists of using an intra-arterial catheter to obtain a precise measurement (continuous blood pressure signal); unfortunately, this invasive practice can lead to pain and infections [4]. The indirect method, based on korotkoff sounds, provides an easy, noninvasive, but less accurate way to measure blood pressure, wrapping a cuff around the upper part of the arm. First, the cuff is inflated with a pressure well above systolic pressure and then gradually reduced. Then, when the pressure in the cuff is equal to the arterial blood pressure, the korotkoff sounds become audible through the stethoscope: the first noise heard corresponds to the systolic blood pressure; by further reducing the pressure, the noises will initially become more intense, and then gradually weaker: the complete disappearance of the noises corresponds to the diastolic blood pressure [5]. This is the operating principle of an ordinary sphygmomanometer, the most common indirect BP measuring method.

Because of the disturbances involved in the invasive method and the discomfort of the noninvasive one, different studies have investigated cuff-less techniques able to measure arterial blood pressure. Among these, Pulse Wave Velocity (PWV) propagation estimates blood pressure values by using the mathematical description by Moens and Korteweg [6]. In [7] it is shown the inverse proportionality between the blood pressure value and the PWV. However, in this case, the proposed mechanical-mathematical model uses patient physiological parameters that are difficult to detect, such as the artery diameter or the distance from heart to fingertip. Pulse Transit Time (PTT), defined as the time the pulse wave takes to travel between two arterial sites within the same cardiac cycle, is another attribute for blood pressure estimation process [8]. The model proposed by [9] overcomes the problem of the availability of the patient's physiological parameters; however, the mathematical relation between PTT and BP is subject to approximations, which make the model not very general and robust.

Our proposed model, solves the generalization problem with the use of an artificial neural network (ANN), called ABPNet. By training it to tackle a regression problem, ABPNet is able to learn the physiological relation that exists between the inputs, i.e. electrocardiographic (ECG) and photoplethysmographic (PLETH/PPG) signals, and the output (ABP). As demonstrated in the following, this approach overcomes the limits of both the noninvasive mathematical-based and the invasive models; indeed, albeit it is still a noninvasive technique, its performances are comparable with the invasive methods and does not require a cuff to be inflated, which, as proven above, is quite uncomfortable for the users.

After the description of the methodology used in this study in Sec. II, in terms of chosen dataset, architecture and metrics, Sec. III shows and discusses the results, comparing ABPNet performances both to invasive (IBP) and noninvasive (NIBP) techniques. Sec. IV presents an application of the proposed method to a real wearable device, the VITAL-ECG. Finally, Sec. V yields the conclusions.

II. METHODOLOGY

As explained at the end of Sec. I, the aim of this research is to derive the underlying relation between ECG and PPG signals with the arterial blood pressure, measured in a noninvasive manner. At this purpose, it has been chosen to exploit the generalization and pattern recognition properties of neural networks. In order to increase the accuracy of the model, ABPNet was trained using invasive blood pressure (IBP) as target and both ECG and PPG as inputs. Then, in the recall phase, the network outputs were compared with those of a certified sphygmomanometer to assess its performances in the noninvasive paradigm.

The trained model will be embedded in the VITAL-ECG [10] wearable device to provide it with an anytime, everywhere, unobtrusive blood pressure measurement feature. Indeed, due to the use of IBP during training, VITAL-ECG will be able to relate properly the acquired ECG and PPG signals with its corresponding ABP values (systolic and diastolic) even if it is used in a noninvasive way.

A. Dataset Description

The proposed approach requires a dataset where ECG, PPG and ABP (acquired both as IBP and NIBP) signals were acquired simultaneously and, most of all, synchronously. Therefore, it has been chosen to use MIMIC, a multi-parameter database where clinical data are obtained from the patient's medical record [11], [12]. As shown in Fig. 1, signals are acquired in synchronized mode. Arterial Blood Pressure is used to train the network with an invasive measure, so that the signal value can be tracked at any time. The ABP signal will be used as a target in the estimation of systolic and diastolic blood pressure values. In this study, the signals of thirty-seven people have been used for training. Each record contains the three signals in a 600 s (i.e. 10 minutes) time window.

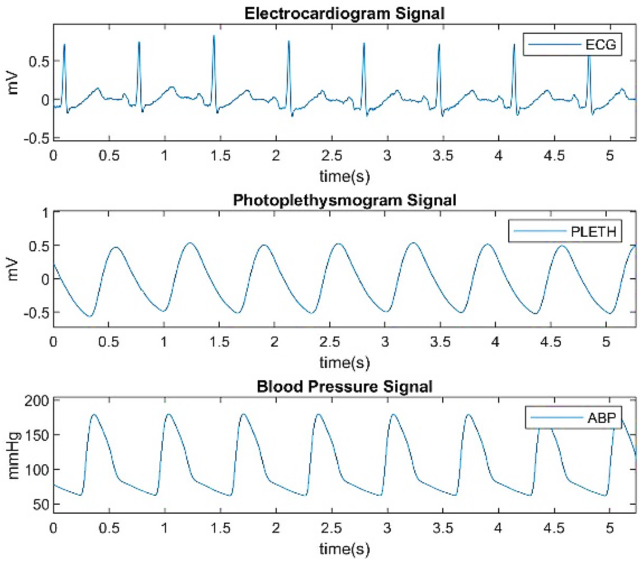

Fig. 1. Synchronized signals representation: ECG (top), PLETH/PPG (center), ABP (bottom).

A noninvasive arterial pressure value is associated with each patient. In this way, the comparative analysis between the sphygmomanometer measurement (gold standard noninvasive tool) and our method can be carried out.

B. Neural Network Architecture

Neural networks (NNs) are a set of algorithms, modeled on the human brain functions, designed to recognize patterns that represents the relationship between the input and the output (target) signals [13]. Fig. 2 shows the standard multilayer perceptron configuration. The input layer corresponds to the number of inputs to the neural network. This layer consists of passive nodes, which do not take part in the actual signal modification, but only transmits the information to the following layer. The hidden layer has arbitrary number of neurons. The nodes take part in the signal modification by means of the activation function. The output layer improve the end results of the iterative process [14].

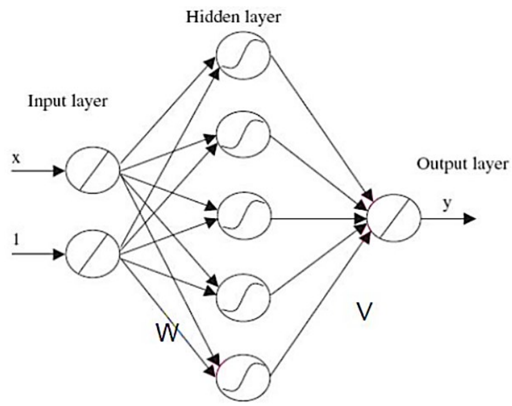

Fig. 2 Multilayer percpetron configuration.

A feed-forward fully connected neural network with two hidden layers, that is, a multi-layer perceptron (MLP), has been designed using MATLAB® R2018b [15] and trained for 50 iterations on a single CPU of LENOVO Y50-70 workstation with 16 GB RAM. Different hidden layer sizes have been tested to evaluate the corresponding network regression performance. Fig. 3 shows the optimal architecture, which has 15 and 8 neurons in the first and second hidden layer, respectively. The inputs are the entire ECG and PPG recordings of each of the 37 patients; the outputs is the blood pressure signal (ABP), synchronized to the two input signals. The hyperbolic tangent was used as transfer function for the hidden layers, while for the output regression layer, the linear function was chosen. The Levenberg–Marquardt algorithm (LMA) is implemented, which is normally adopted to solve generic curve-fitting problems. This fitting algorithm is quite performing in this kind of task because it finds local minimum; indeed, it can be seen as trade-off technique between the Gauss–Newton algorithm (GNA) and the method of gradient descent [16]. For training the networks, both the input and target vectors have been randomly divided into three sets as follows: 70% for training, 15% to validate that the network is generalizing and to stop training before overfitting, and the remaining 15% is used as a completely independent test set for network generalization. Finally, the backpropagation [17] was applied as learning algorithm and the k-fold cross validation method [18] was used to evaluate the validity of the model.

C. Metrics

In a regression problem, such as the ABP estimation case, it is important to measure the resemblance of the output w.r.t the desired target. The goal is to have a neural network able to approximate the target (ABP) accurately. To assess the validity of the model, both Pearson correlation coefficient (*r*) and Root Mean Square Error (*RMSE*) between the desired data and the predicted data were chosen as metrics because of their pointwise nature.

The Pearson's correlation coefficient measures the statistical relationship between two continuous variables, using the covariance method [19]. It is defined as follow:

$$r = \frac{n * \sum_{i=1}^{n} y_i * \tilde{y}_i - \sum_{1=1}^{n} y_i \sum_{1=1}^{n} \tilde{y}_i}{\sqrt{[n * (\sum_{1=1}^{n} {y_i}^2)] - (\sum_{1=1}^{n} y_i)^2] * [n * (\sum_{1=1}^{n} {\tilde{y}_i}^2) - (\sum_{1=1}^{n} \tilde{y}_i)^2]}} \quad (1)$$

where y is the desired output (target), $\tilde{y}$ is the predicted values and n is the total number of data. It is ranged between $[-1, 1]$: $r = 1$ indicates perfect positive correlation between y and $\tilde{y}$; $r = -1$ perfect negative correlation; $r = 0$ no correlation.

Another method used to evaluate the efficiency of the prediction model is the Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i}^{n} (y_i - \tilde{y}_i)^2} \quad (2)$$

RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are. If the correlation coefficient is 1, the RMSE will be 0, because all of the points (that represents predicted variables) are set on the regression line [20].

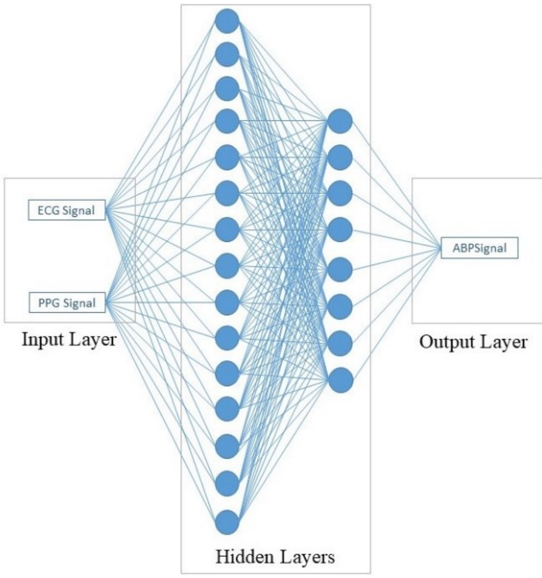

Fig. 3. ABPNet architecture

III. Results

Given the continuous blood pressure signal (i.e. IBP), it is necessary to gather values that can be transformed, respectively, to the diastolic (DBP) and systolic (SBP) blood pressures. At this purpose, the signal need to be analyzed, filtered with a low pass filter (cut-off frequency equal to 200 Hz) to remove noise, and, finally, the characterizing points can be extracted. Fig. 4 shows an example of a signal window (roughly from 276 s to 279 s), where are highlighted the significative points of an ABP signal needed to compute both diastolic and systolic pressures:

- the systolic phase, characterised by a rapid increase in pressure up to a peak, represents the systolic blood pressure. This phase begins with the opening of the aortic valve and corresponds to the left ventricular ejection;

- the notch to the dicrotic peak, which represents the closure of the aortic valve;

- the diastolic phase, which represents the Diastolic blood pressure and describes the run-off of blood into the peripheral circulation.

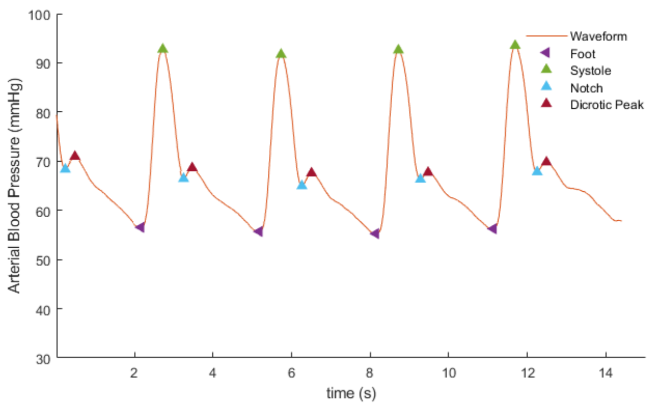

Fig. 4. Continuous arterial blood pressure filtered signal: foot point (violet), systole point (green), notch point (blue), dicrotic peak (red).

For each patient, both the target signal used for training and the network output are, actually, represented by a continuous ABP signal. To obtain a discrete, single value of SBP and DBP, the signal points of interest (systoles and feet) were identified and averaged to obtain two single pressure values, i.e. systolic and diastolic pressures, referred to the whole arc of the recording. This procedure was applied both for the target and the output signal yielded from the network.

A. *ABPNet regression performances analysis*

A regression plot between targets and outputs measures the predictive capability of a regression model, such as ABPNet. Pearson *r* coefficient indicates how close the data are, on average, to the fitted regression line.

Fig. 5 shows the regression plot for diastolic and systolic ABP data for each of the 37 patients of the training dataset. The solid line, blue (left) or green (right), represents the overall fitting curve, while the circles indicate the computed output ABP, either diastolic or systolic, w.r.t. the target invasive one. The predictive ability of ABPNet is very accurate because the regression line is quite indistinguishable from the dotted line $Y = T$, which represents the perfect regression. Indeed, the Pearson *r* coefficient is close to 1 for both diastolic and systolic (0.93 and 0.97, respectively).

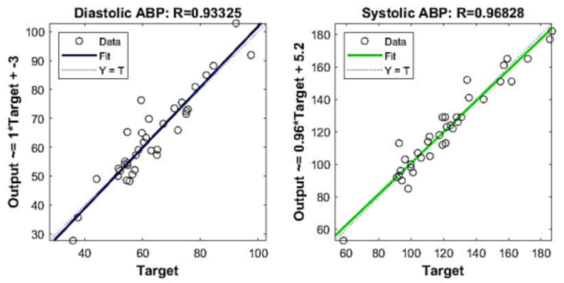

Fig. 5. Regression plot of diastolic (left) and systolic (right) ABP data

B. *ABPNet and invasive method comparison*

To further analyze the performances of the network w.r.t the invasive blood pressure, the values (DBP and SBP) extracted from the reference signal (IBP) and the network output were compared for all the subjects. In Fig. 6 these two signals (IBP targets in blue and ABPNet outputs in red) are plotted together. Their overlapping demonstrates that the ABPNet predicted ABP values, i.e. its outputs, closely match the invasive values, i.e. the targets. Moreover, this consideration holds for almost each patient with the exception of patient 32 in the diastolic case and patient 5 in the systolic one.

C. *ABPNet and noninvasive method comparison*

The above analysis have proven the validity of the proposed approach w.r.t the invasive blood pressure measurements, both in terms of neural regression and accuracy of prediction. This subsection presents the comparison between sphygmomanometer BP values, i.e. the noninvasive gold standard, and the ABPNet output w.r.t. those computed from the IBP method, which yields, by definition, the most accurate measurements. Therefore, the aim is to use the invasive measurement as a benchmark and to compare the two noninvasive techniques, ABPNet and sphygmomanometer, against it. The two approaches were evaluated using the chosen metrics: *RMSE* and *r*; Table I summarizes the results: left part compares the sphygmomanometer with the IBP reference, while on the right, the similarities between ABPNet and IBP are analyzed.

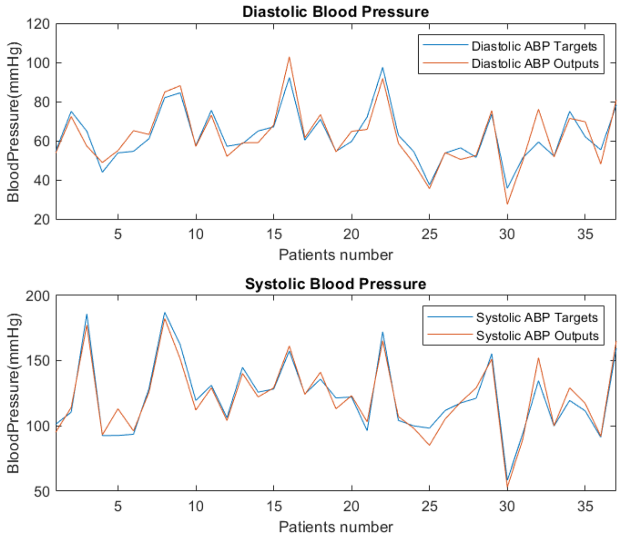

Fig. 6. Diastolic blood pressure (top) and systolic blood pressure (bottom) estimation performance diagram between IBP targets (blue) and ABPNet outputs (red)

ABPNet outperforms the sphygmomanometer noninvasive gold standard demonstrating a higher reliability than ordinary noninvasive pressure detection methods. Indeed, for both DBP and SBP, the ABPNet RMSE is lower (3.2 and 3.6) and the Pearson coefficient is much closer to 1 (0.93 and 0.97). Therefore, the proposed method, and consequently the VITAL-ECG device, would comply with the ANSI/AAMI/ ISO 81060- 2:2013 (the legislation for sphygmomanometer certification) because the ABPNet values are within +/- 5 mmHg w.r.t. the real invasive measurements.

TABLE I. RMSE AND PEARSON'S COEFFICIENT FOR SPHYGMOMANOMETER AND ABPNET EVALUATED ON THE TEST DATASET

Metric	**Sphygmomanometer**		**ABPNet**	
	DBP	***SBP***	***DBP***	***SBP***
r	0.90	0.89	0.93	0.97
RMSE (mmHg)	4.1	4.7	3.2	3.6

IV. VITAL-ECG

As final stage of the research, the proposed neural algorithm will be embedded in the VITAL-ECG [10], a wearable device, developed in the Neuronica Lab of Politecnico di Torino, able to record simultaneously, among the others, ECG and PPG signals (see Fig. 7). It has been designed accordingly to the IoT paradigm for smart, wearable healthcare devices for telemedicine and, more generally, mobile health. As shown in Fig. 8, VITAL-ECG has the size of a watch and can be comfortably worn from any user at his wrist. It does not require any medical expertise to be placed or used. It just needs to gently touch with two fingers the silver electrode and PPG sensor for 10 s. Then, the system records, stores and sends via Bluetooth the PPG and ECG signals to the mobile App, which analyzes the acquisitions to compute the heartrate and to look for anomalies, i.e. diseases.

If embedded in a device like VITAL-ECG, the proposed noninvasive blood pressure method can be used to fight cardiovascular diseases and prevent their dangerous effects. Indeed, a wearable, unobtrusive systems, such as the VITAL-ECG, allows people to have a simple, easy to use, device to acquire and monitor their blood pressure everywhere, anytime, without the need of specialized personnel, e.g. physicians or professional caregivers.

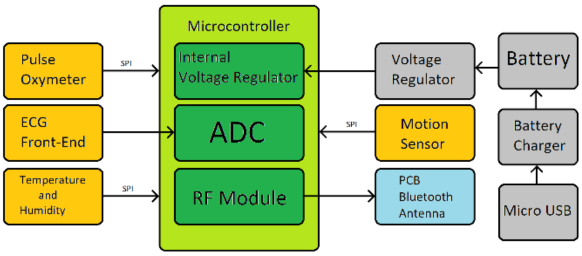

Fig. 7. VITAL-ECG device architecture (block diagram)

Fig. 8. VITAL-ECG device

V. CONCLUSIONS

ABP is an important physiological parameter that must be monitored to prevent and detect cardiovascular diseases. In this paper, a two hidden layer neural network, called ABPNet, was implemented to predict the systolic and the diastolic ABP values. The proposed model is tested on MIMIC database and validated with gold standards both in invasive and noninvasive approaches. ABPNet predictive performances are quite promising: the RMSE and Pearson coefficient of the model outperform those of traditional standard sphygmomanometer. The yielded outputs are compliant with the ANSI/AAMI/ ISO 81060- 2:2013 because they are within +/- 5 mmHg w.r.t. real invasive measurements. Furthermore, the proposed noninvasive blood pressure method can be embedded in wearable, unobtrusive devices, such as the VITAL-ECG, and used to fight cardiovascular diseases and prevent their dangerous effects.

Future works will deal with improving the blood pressure estimation algorithm by increasing the number of data, i.e. the training set, and by testing different type of deep learning approaches, specialized in time series prediction: Long-Short-Term Memory (LSTM) neural network with a regression layer and ResNet. Finally, separate works will embed the algorithm into the VITAL-ECG, so that the wearable device would be able to yield also the blood pressure values, DBP and SBP, and to monitor patient condition more effectively.

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