Deep Visio-PhotoPlethysmoGraphy Reconstruction Pipeline for Non-invasive Cuff-less Blood Pressure Estimation

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Abstract: In medical field, many cardiovascular and correlated diseases can be early treated by monitoring and analyzing the subject's blood pressure (BP). However, the measurement of blood pressure requires the use of invasive medical and health equipment, including the classical sphygmomanometer or the digital pressure meter. In this paper, we proposed an innovative algorithmic pipeline to properly estimate the systolic and diastolic blood pressure of a subject through the visio-reconstruction of the PhotoPlethysmoGraphic (PPG) signal. By means of an innovative method of face-motion magnification through Deep Learning, it is possible to visio-reconstruct specific points of the PPG signal in order to extract features related to the pressure level of the analyzed subject. The proposed approach can be used effectively in healthcare facilities for the fast and non-invasive monitoring of the pressure level of subjects or in other similar applications. We compared our results using a classic cuff-less blood pressure device with encouraging results that reach 92% in accuracy.

1 INTRODUCTION

Monitoring the systolic and diastolic pressure of both healthy and hypertensive subjects is certainly one of the most important aspects for safeguarding subject's health. Many cardiovascular diseases are strictly caused by pressure dysfunctions and therefore can be easily treated if the blood pressure level is kept under control (Wu et al., 2015). In recent years, there has been an increasing interest in measuring blood pressure by taking advantage of simple and non-invasive approaches, some of these are based on the use of the PhotoPlethysmoGraphic (PPG) signal (Dastjerdi et al., 2017). Photoplethysmography is a simple optical technique that can be used to detect changes in the volume of blood in the microvascular bed of tissues (Rundo et al., 2018c). It is not invasive since it makes measurements on the surface of the skin. Based on these assumptions, we designed a Deep Learning (DL) architecture to perform the visio-reconstruction of the PPG signal from the face-motion analysis of the subject, with the aim to extract ad-hoc features correlated to the level of systolic and dias-

tolic pressure. The proposed pipeline can be implemented as an embedded firmware in any smartphone equipped with a video camera and PPG sensing-device (classical Light Emitting Diodes LEDs with Silicon PhotoMultiplier (SiPM) photo-detector device (Rundo et al., 2018c)) and therefore can be applied daily and simply by any subject (Rundo et al., 2018c). In Figure 1, we illustrated the method used to sample the PPG signal as well as the physiological correlation with heart activity and them with blood pressure (Vinciguerra et al., 2018). As shown in Figure 1, the PPG sensing framework (PPG Sensing Device) is composed by a coupled LEDs with SiPM device (photo-detector) with a STM32 based microcontroller for pre-processing the sampled physiological raw data (Vinciguerra et al., 2018). More details in (Rundo et al., 2018c; Vinciguerra et al., 2018). In Figure 1, it is also evident how the PPG signal is strongly correlated to the cardiac activity of a subject (by measurement of changes in blood volume) and then with blood pressure. The remainder of the paper is structured as follows. In Section II we present the related works. In Section III we describe the proposed pipeline while in Section IV we report the experiments we made for validating the proposed approach. Finally, in Section V we report the conclusions.
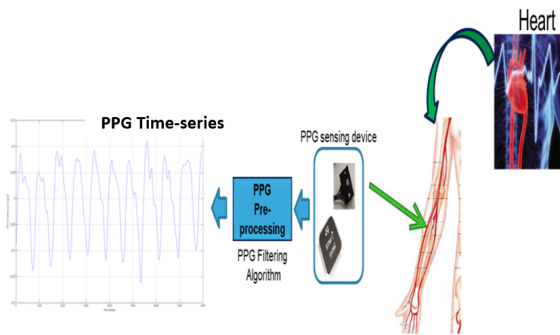
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Figure 1: The PPG signal sampling pipeline.

Figure 2: Example of a LSTM cell.

2 RELATED WORKS

A considerable amount of literature focused on estimating blood pressure or arterial stiffness taking advantage of Deep Learning (DL) methods. In (Monte-Moreno, 2011), the author proposed a non-invasive approach to estimate the systolic and diastolic blood pressure by using PPG. The experimental results shed light on relationship between blood pressure, glucose levels and PPG waveform confirming the effectiveness of Machine Learning (ML)-based techniques. In addition to these techniques, specialized ML-based methods have been proposed with the recent emergence of Deep Learning. Slapnicar et al. (Slapničar et al., 2019) investigated the problem of detecting Blood Pressure (BP) using a ML-based architecture. In order to overcome limitations derived from using cuff-based devices, the authors used PPG and its first and second derivative to feed a novel spectro-temporal Deep Neural Network (DNN). Finally, they performed a leave-one-subject-out experiments confirming the advantage of the proposed model in computing dependency between PPG waveforms and blood pressure. In (Alty et al., 2007), the authors proposed a ML-based pipeline to predict arterial stiffness i.e. and an indicator correlated to blood pressure. It is reliable for the classification of subjects into high and low aortic pulse wave velocity (PWV) aiming to analyze cardiovascular disease. Their work highlights the effective results achieved by Support Vector Machine (SVM) not only for classification purpose but also in performing multilinear regression. In (Rundo et al., 2018b), the authors described an innovative approach to estimate cardiovascular disease risk via blood pressure. The proposed method measures BP by analyzing the PPG signal without requiring any user calibration. In (Huynh et al., 2018), the authors proposed an interesting approach to estimate the blood pressure by using averaging Impedance Plethysmography (IPG) for detec-
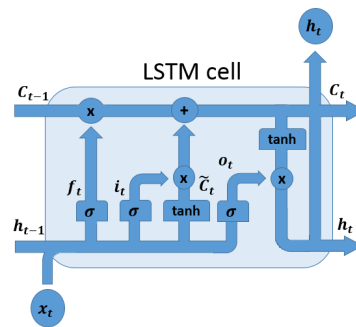
tion of Pulse Transit Time (PTT). The experimental estimation of blood pressure (BP) provided very interesting results (RMSE: 8.47 ± 0.91 mmHg and $5.02 \pm 0.73 mmHg$ for systolic and diastolic level, respectively). Despite providing effective results, the aforementioned approaches require the use of invasive medical devices throughout the measurement of blood pressure levels. In this work, the authors proposed a less-invasive and cuff-less approach for measuring blood pressure.

3 BACKGROUND AND THE PROPOSED PIPELINE

In this paper, a novel Deep Long Short-Term Memory (LSTM) based pipeline is presented. The LSTM Vanilla architecture was originally proposed by Hochreiter and Schmidhuber (Hochreiter and Schmidhuber, 1997) for preventing the Vanishing gradient problem which affects Recurrent Neural Networks (RNNs). The LSTM cell is able to select what information to discard or store. In order to produce effective results in real-applications, this selective method requires three different mechanism to read, store and discard information by taking advantage of specific vectors called "gates". Basically, the "input gate", "output gate" and "forget gate" decision is implemented via activation functions which define if a given information is relevant or not. More in details, given x_t as input vector, h_{t-1} as previous cell output, C_{t-1} previous cell memory, h_t as current cell output and C_t as current cell memory, we define Equations (1)-(3) to determine what information to store. Finally, we generate the output of LSTM by updating old cell state as per Equation (4) and merging the previous output, the input and the bias vector as Equations (5)-(6).

$$f_t = \sigma(W_f \circ [h_{t-1}, x_t] + b_f \qquad (1)$$

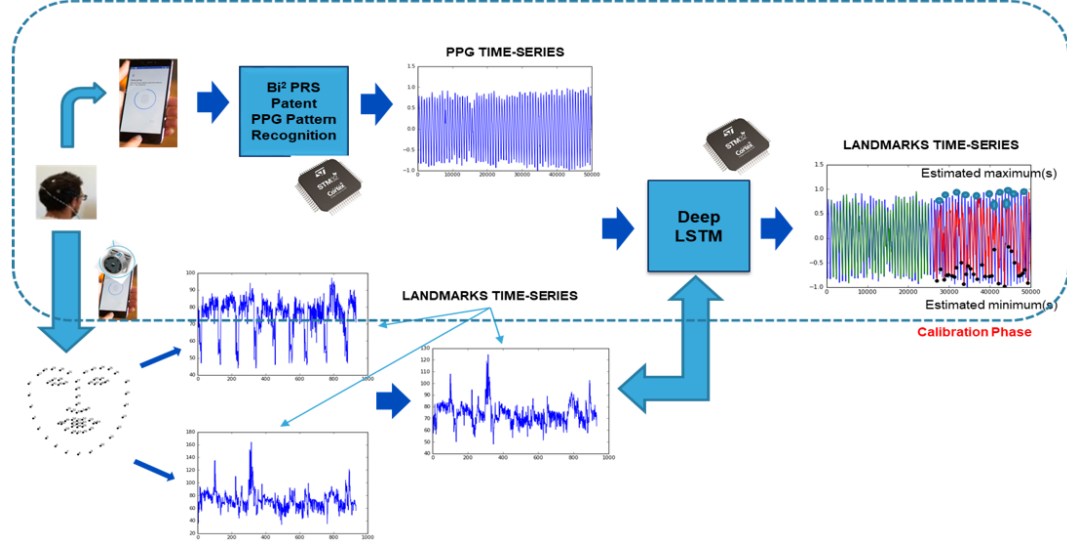$$i_t = \sigma(W_i \circ [h_{t-1}, x_t] + b_i \qquad (2)$$

Figure 3: The proposed Deep LSTMs pipeline.

$$\widetilde{C}_t = \tanh\left(W_C \circ [h_{t-1}, x_t] + b_C\right) \quad (3)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o \circ [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t * \tanh(C_t) \quad (6)$$

In Figure 2, a prototype of LSTM cell is reported. In recent years, several LSTM-based approaches have been developed with promising results. For instance, LSTM architectures have been largely employed in automotive field to visio-reconstruct such part of the car-driver PPG signal (sampled by ad-hoc sensors placed in the steering) when this physiological signal was no longer available (Trenta et al., 2019). Inspired by recent literature, we designed a Deep LSTM pipeline aiming to better visio-reconstruct the PPG waveforms of a subject in order to estimate the correlated blood pressure. The proposed system architecture consists of a physical signal-acquisition module (PPG sensing device) needed for preliminary calibration as well as a vision module to extract effective facial descriptors and a Machine Learning framework that reconstruct such part of the PPG waveforms (extremes points such as minimum, maximum and so on) in order estimate the blood pressure (BP). During the calibration phase of the proposed system, the PPG signal is collected by using a coupled LED-SiPM sensing system available in several medical devices or smartphones and able to generate the PPG raw data (Rundo et al., 2018a; Rundo et al., 2017). Then, we apply the patented Bi2PRS algorithm to obtain the filtered compliant PPG signal. The Bi2PRS algorithm (Rundo et al., 2018a) is able to properly filter the collected PPG raw data (by means of an ad-hoc Butterworth band-pass filter) and then to determine, in the filtered PPG waveforms, the right value of the extreme points such as max, min, etc. More details on Bi2PRS in (Rundo et al., 2018a; Rundo et al., 2017). During the PPG sampling session, we recorded a video sequence of the subject by using a smartphone having a camera device with 30 fps as frame-rate, under high light condition. As widely known in scientific literature (Oh et al., 2018), the face of the subject performs visual micro-movements imperceptible at naked eye and closely related to the cardiac pumping activity. These micro-movements are strongly correlated to PPG signal as a cardiac related signal. Inspired by the work of Wu et al. (Wu et al., 2012), in which the authors introduced Video Magnification to amplify facial micro movements for revealing the flow of blood, we proposed an approach in which a group of video frames (face sequences of the subject) are extracted and then analyzed in order to identify such facial landmarks to be tracked (through the pixel intensities over time). Specifically, we designed input layer of the proposed Deep LSTM model for processing facial landmarks of both eyes. In Figure 3, we have summarized the overall scheme of our proposed pipeline. More details in the next paragraphs. The framework of the proposed Deep LSTM architecture is composed by one input layer, three hidden layers, and one output layer. Specifically, we designed three hidden layers which include two regular layers and one dropout layer appointed to boost the overall performance. The model was trained with an initial learning rate of 10^{-3}. The batch size was set to 512 and the maximum number of train-

ing epochs was set to 100. During the calibration phase, we trained the designed Deep LSTM to analyze the correlation between the facial time-evolution selected landmarks of the subjects with correlated extreme points of the PPG signal. The output of the LSTM pipeline represents predicted extreme points of the PPG signal considering the facial landmarks time series. When the proposed Deep LSTM framework has learned the correlation between facial landmarks and extreme points of the subject's PPG signal, the calibration phase will be dropped and therefore the system will operate feed-forward in the vision part only linked to the acquisition of facial landmarks only. The calibration phase of the device requires few minutes of acquisition of the PPG signal (and corresponding visual data) and it will be necessary to perform it only once. On the other hand, the trained feed-forward system (only Visio-based Deep LSTMs pipeline followed by reconstructed PPG extreme point(s) classifier, as described in the section IV) is able to generate the output (blood pressure estimation) in a near real-time context (few seconds). The so designed pipeline was ported to the STM32 architecture through the STM32-CUBE AI software platform. In Figure 4, a graph reporting the estimated extreme points by the proposed trained Deep LSTM super-imposed with original source PPG signal is shown. Once we have collected the set of characteristic extreme points of the waveforms of the PPG signal, we are able to characterize the subject's cardiac activity with regard to the two phases of the cardiac cycle i.e. systole and diastole, on which the level depends on blood pressure. In Figure 5, we reported a classical PPG waveform and the corresponding dynamic correlated to the cardiac cycle. By means of the characteristic PPG visio-reconstructed extreme points (*m1*, *m2*, *m3*, *m4*), we are able to estimate the heart systole and diastole phases, therefore, the pressure levels related to them. For each pair of PPG waveforms (PPG^j, PPG^{j+1}) we define the following indicators:

$$\varphi = [m_1^j, m_2^j, \ m_3^j, m_4^j, dx_i^j, dy_i^j, mAI^J]$$

$$\forall \ j = 1..N^{PPG} - 1 \ ; i = 1, 2, 3, 4 \qquad (7)$$

$$m_i^j = (x_{m_i^j}, y_{m_i^j})$$

$$\forall \ j = 1...N^{PPG} - 1 \ ; i = 1, 2, 3, 4 \qquad (8)$$

$$dx_i^j = x_{m_i^{j+1}} - x_{m_i^j}$$

$$\forall \ j = 1...N^{PPG} - 1 \ ; i = 1, 2, 3, 4 \qquad (9)$$

$$dy_i^j = y_{m_i^{j+1}} - y_{m_i^j}$$

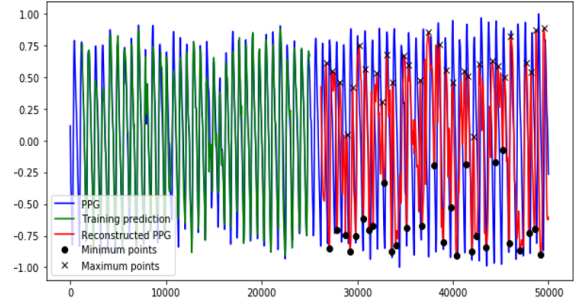$$\forall \ j = 1...N^{PPG} - 1 \ ; i = 1, 2, 3, 4 \qquad (10)$$

Figure 4: The reconstructed extreme points super-imposed to the corresponding source PPG signal.

$$mAI^j = ((y_{m_3^j} - y_{m_1^j}) - y_{m_4^j})/(y_{m_3^j} - y_{m_1^j}) \qquad (11)$$

where mAI^J is a modified version of the so-called Augmentation Index usually computed for measuring the arterial stiffness (Gonzalez et al., 2012) while NPPG represents the number of PPG waveforms. The other indicators reported in the Equations (8)-(10) allow us to characterize cardiac cycles (and therefore the relative pressure levels) according to the PPG signal mapping reported in Figure 5. The elements of the vector φ represents the input of a machine learning framework (Fully Connected Multi-Layers Network with binary output) designed to learn the correlation between the so computed input elements and the corresponding value of the systolic and diastolic blood pressure. The output of the machine learning framework is a binary value which can be considered as a discriminating flag to indicate if the subject presents normal pressure values (0) or not (1). The set 120/80, which indicates 120 mmHg for systolic pressure and 80 mmHg for diastolic pressure, has been considered as normal blood pressure values. Under the supervision of a team of physiologists, we have defined all pressure values less than or equal to 120/80 as acceptable blood pressure while higher values are considered anomalous and as such must be signaled and monitored. It should be noted that the proposed system can monitor and discriminate even different pressure levels (with respect to the classic 120/80 mmHg) requiring a different and adequate calibration. The proposed pipeline has been tested and validated as described in the following paragraph.

4 EXPERIMENTS

In order to train and validate the proposed system, under the supervision of the physiologists who collaborated with us in this work, we have collected a dataset of subjects to perform systolic and diastolic pressure measurements simultaneously with the acquisition of
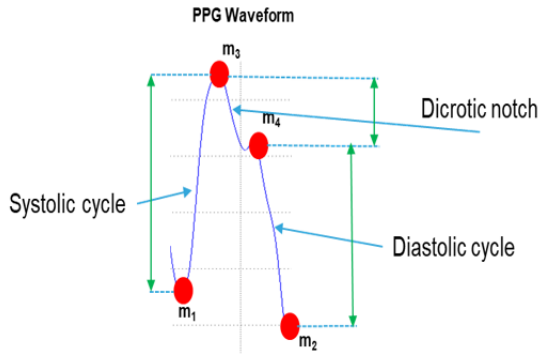
Figure 5: The reconstructed extreme points super-imposed to the corresponding source PPG signal.

the PPG signal and contextually the video sequence reporting the subject's face. The blood pressure measurements were performed using a classic certified medical sphygmomanometer. All procedures were carried out under the supervision of the physiologists and after we have received the informed consent of each patient and having acquired the consent from the Ethical Committee CT1 (authorization n.113 / 2018 / PO), which were conducted in accordance with the Declaration of Helsinki. The dataset is composed of 56 both healthy and hypertensive subjects including both males and females individuals. The minimum age of the subjects in the dataset is 21 years while the maximum age is 70 years. The collected minimum pressure value is around 110/75 while the maximum pressure value is 140/85. For each subject, systolic and diastolic pressure was acquired as well as a few minutes (5 min) acquisition of PPG signal and video signal (subject face), as above described. The acquisitions of the PPG signal, needed for the preliminar calibration and training of the whole pipeline, were performed at a sampling frequency of 1 kHz and by using the system described in (Rundo et al., 2018a). We designed a Fully Connected Network (FCN) trained with the Scaled Conjugate Gradient backpropagation (SCG) algorithm described in (Møller, 1993) with a unique hidden layer of 500 neurons. The designed FCN learns as input the visio-reconstructed PPG extreme points while the output is a binary flag confirming if the corresponding blood pressure is normal (0) or not (1). In Figure 6, we reported the learning error dynamic of the proposed machine learning framework as well as the ROC curves both in training and validation. The dataset has been divided as follow: 70% of the data has been used for the training activity while the remaining 30% for testing and validation. In order to robustly validate the proposed method, we calibrated the proposed pipeline for all subjects of the training and validation dataset and then we created tests consisting of multiple frames
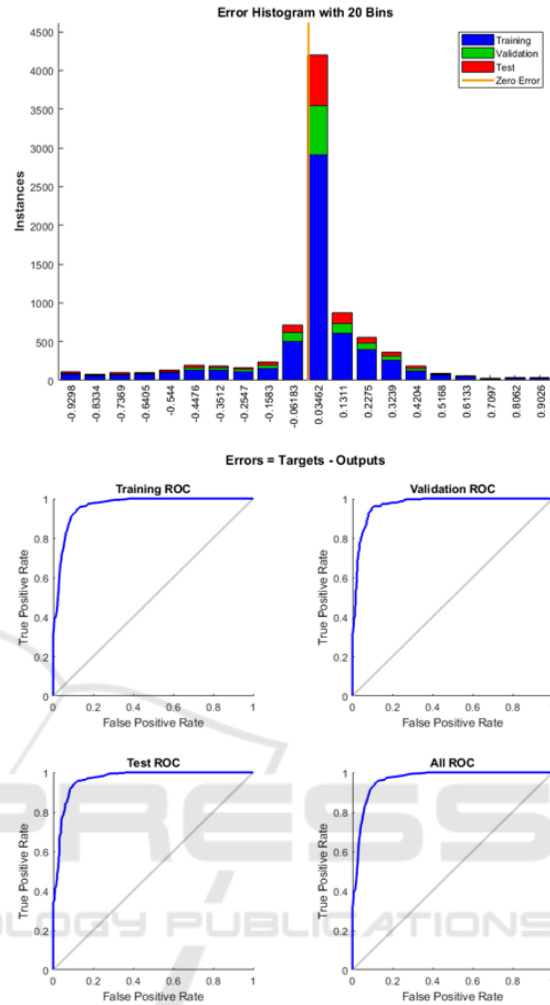

Figure 6: (a) Learning error dynamic histogram of the Machine Learning classifier (b) ROC curves both in validation and training dataset.

of the subjects that are sequentially and randomly fed to the Machine Learning system (for each subject we initialize the machine learning system with related weights computed during calibration). For each patient, we reconstituted the characteristic extreme points of the PPG signal which were then fed to the machine learning framework for classifying the corresponding blood pressure level. The total accuracy (in test set) of the proposed system in discriminating normal-pressure subjects from subjects with blood pressure higher than normal or hypertensive is 91.7%.

5 CONCLUSIONS

The obtained results are very promising in the field of medical-health applications for the early prevention of cardiovascular pathologies. The main benefit of the proposed system is the non-invasive and effective estimation of the subject's blood pressure level in few seconds. The experimental results allow us to be confident about the applicability of this approach in different applications in the medical field. Future works will focus on collecting more data in order to improve the effectiveness of the proposed approach as well as to implement a robust pipelines for monitoring the response to certain oncological treatments (such as chemotherapy and immunotherapy) as many anti-neoplastic drugs are known to produce abnormal increases in blood pressure which therefore requires continuous monitoring and within acceptable times (Banna et al., 2018; Rundo et al., 2019).

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