On Evaluating Blood Pressure Through Photoplethysmography

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Abstract. This paper investigates the hypothesis that a nonlinear relationship exists between photoplethysmography (PPG) and blood pressure (BP) values. Trueness of this hypothesis would imply that, instead of measuring a patient's BP in an invasive way, this could be indirectly measured by applying a wearable PPG sensor and by using the results of a regression analysis linking PPG and BP. Genetic Programming (GP) is well suited to find the relationship between PPG and BP, because it automatically evolves the structure of the most suitable explicit mathematical model for a regression task. In this paper, for the first time, some preliminary experiments on the use of GP to explicitly relate PPG and BP values have been performed. For both systolic and diastolic BP values, explicit nonlinear mathematical models have been achieved, involving an approximation error of less than 3 mmHg in both cases.

Keywords: Blood pressure · Wearable sensors · Photoplethysmography · Regression · Genetic programming

1 Introduction

Arterial blood pressure can be continuously measured in real time and with no patient's body cannulation by means of the continuous non-invasive arterial pressure (CNAP) method. This method shows the positive features of two clinical "gold standards": firstly, the Blood Pressure (BP) is continuously measured in real time as it takes place in the invasive arterial catheter system, and secondly it is non-invasive as it is the case for the standard procedure based on upper arm sphygmomanometer.

Currently a high demand exists for accurate and easy-to-use CNAP-systems. Because of this, there is an increasing focus on these devices. The development of efficient BP measurement instruments is facilitated by the use of small yet powerful microcomputers, and by that of digital signal processors as well. Small, cheap devices of this kind allow for an easy processing of complex and computationally intensive mathematical functions.

This paper hypothesizes the existence of a nonlinear relationship between PPG and BP values. Trueness of such a hypothesis would imply that, instead of measuring a patients BP in an invasive way, both systolic and diastolic BP

B. Mandler et al. (Eds.) IoT 360° 2015, Part I, LNICST 169, pp. 523–529, 2016.
DOI: 10.1007/978-3-319-47063-4_57

values could be indirectly measured by applying a wearable wireless PPG sensor to patients finger and by making use of the results of a regression analysis linking PPG and BP values. Genetic Programming (GP) [1] is well suited to find the relationship between PPG and BP, because it automatically evolves the structure of the most suitable explicit mathematical model for a regression task.

An analysis of the related scientific literature shows that this is the first attempt to explicitly relate PPG and BP values through GP. Some papers exist in which the aim is the investigation of the relationship between the blood pressure and some other variables, for example [2–6]. Very recently, we proposed a noninvasive approach relying on the hypothesis of the existence of a nonlinear relationship between PPG and heart activity (and thus ECG and Heart Rate Variability -HRV- parameters), and BP [7]. GP was used to find this explicit relationship. Results were very promising, the approximation error on unseen data being slightly lower than 2 % for both BP values. With respect to that paper, the novelty in the current paper is that just one PPG sensor is used, aiming at improving non-invasiveness and ease of use.

2 The Study

To realize the mathematical model, a study has been conducted on a group of 11 healthy subjects, with a mean age of 34.18 years (range 28–54 years), enrolled in accordance with the following selection criteria, namely that they were:

- not suffering from any pathological cardiovascular conditions, neurological or psychiatric disorders or other severe diseases;
- not taking any medication at the time of the study;
- had not taken any caffeine or had not smoked any cigarette in the 2 h prior to the measurements.

During the study, a PPG signal was monitored using a wearable oximeter sensor, the NONIN 9560 onyx 2 Bluetooth finger pulse oximeter. The BP values were measured with a digital sphygmomanometer, the A&D Medical Upper Arm Blood Pressure Monitor UA-767PBT-Ci, with the left arm comfortably positioned on a horizontal surface and the cuff positioned at the level of the heart at about 2 cm from the inner side of the elbow.

The experiments were carried out in a quiet room, with dimmed lighting and a comfortable temperature of about 23 °C. During the study the volunteers were invited to sit in a comfortable position, without crossing their legs, for 5 consecutive minutes. During this phase, systolic and diastolic BP was recorded five times, with a 60 s interval, and the PPG was continuously recorded during these 5 min. The acquired PPG signal is processed using a Matlab script developed by us to automatically calculate the minimum and the maximum values from the PPG waveform, as shown in Fig. 1.

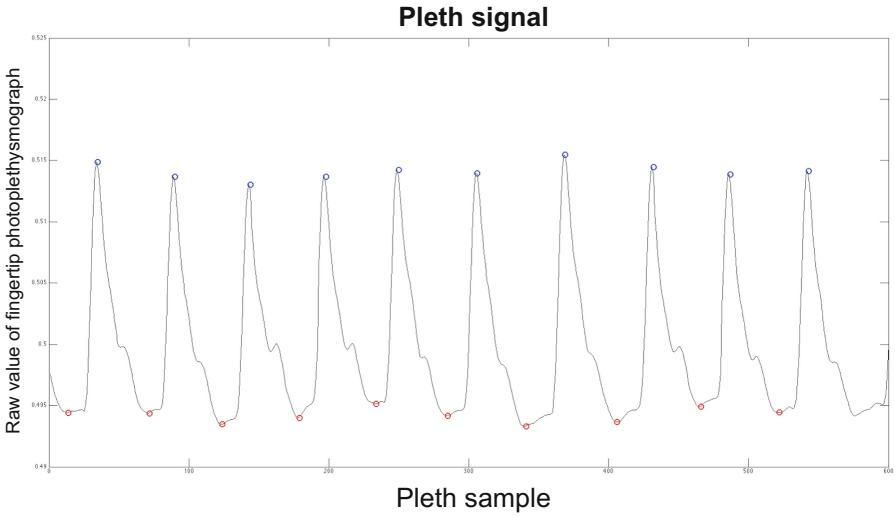

Fig. 1. An example of a record contains the PPG waveform: blue circles indicate the maximum PPG values, and red circles the minimum PPG values.

2.1 The Database

Our database contains the BP measurements and the PPG measurements. It is composed by 10 instances for each subject. Each instance i makes reference to 30 s, and is constituted by the following information:

- sub_id: a number value to identify the subject;
- $SBP(i)$: the Systolic BP value measured in the i-th 30-s time slot;
- $DBP(i)$: the Diastolic BP value measured in the i-th 30-s time slot;
- $Pl_M(i)$: the average of the maximum values of PPG signal computed in the i-th 30-s time slot;
- $Pl_m(i)$: the average of the minimum values of PPG signal computed in the i-th 30-s time slot;

Both systolic and diastolic BP values were recorded with a 60–s interval, due to inflation/deflation times of the sphygmomanometer cuff, whereas database items make reference to 30–s intervals. Therefore each recorded value is assigned to a pair of consecutive items.

In this paper we have enrolled 11 patients, six female and five male, so our database contains 110 instances in total.

3 Experiments

For the experiments described in this paper GPTIPS [8], a GP tool working under MATLAB, has been used. To create the regression functions, a set of 11

elementary functions has been considered, including the four arithmetical ones ($+$, $-$, $\cdot$, $/$), two trigonometric ones (sin, cos), hyperbolic tangent (tanh), the exponential (exp), the square value (sqr), the protected square root (psqroot) and the protected logarithm (plog) (see [7] for details).

The database has been divided into train, validation, and test sets. The train set contains the items onto which the approximation of the actual output values will be carried out in the learning phase. The generalization ability of the model achieved is, instead, evaluated on the validation set. Finally, the real evaluation of algorithms performance is carried out over the test set. For each patient, each item has been randomly and exclusively assigned to one of the three sets in this way: 44 % for the train set, 24 % for the validation set, and 32 % for the test set.

GP is a nondeterministic algorithm, which means that its execution and its results depend on the initial value assigned to a random seed. In order to get rid of this feature, the GP algorithm has been run over the database 25 times. Among the 25 runs, we consider as the best one that in which the lowest Root Mean Square Error (RMSE) value over the validation set has been achieved. In fact, the model found in that run shows the best ability to correctly get totally unknown data, so it has the highest generalization capability.

The formula achieved in the best run for the systolic blood pressure is:

$$\begin{aligned} SBP = {} & 21.75 \cdot sin(sin((12.79 \cdot Pl\_M)/Pl\_m)) \\ & - 12.52 \cdot sin((12.92 \cdot plog(tanh(Pl\_M)))/Pl\_m^2) \\ & - 5188.0 \cdot cos(-Pl\_M^2 + plog(Pl\_m) + plog(Pl\_m - 82.88)) \\ & - 4403.0 \cdot tanh(sin(cos(plog(Pl\_M)))) - 2201.0 \end{aligned}$$

Fig. 2. Results for the systolic blood pressure.

Figure 2 reports how this formula allows fitting the real systolic BP values. The top pane shows the behaviour over the train set, the middle pane that over the test set, and the bottom pane that over the validation set.

The results over the test set, i.e. over data never learned by the GP algorithm, are very good, and the RMSE is 8.49. This means that, on average, over previously unseen data any actual systolic BP value and the corresponding computed one differ by $\pm\sqrt{8.49} = \pm 2.91$ mmHg, which is a good approximation.

The formula achieved in the best run for the diastolic blood pressure is:

$$\begin{aligned} DBP = {} & 88.3 - 27.74 \cdot psqroot((Pl_m - sin(Pl_M))/sqr(sqr(Pl_m))) \\ & - 5.97 \cdot plog(((Pl_m - sqr(Pl_M)) \cdot (Pl_m - Pl_M))/sqr(Pl_m)) \\ & - (196.4 \cdot (Pl_m - sin(Pl_M)) \cdot (sqr(Pl_m) + sqr(Pl_M))^2)/(Pl_M - sin(Pl_m)) \\ & - 127.7 \cdot psqroot(Pl_M + plog(Pl_m) + Pl_m \cdot Pl_M) \end{aligned}$$

Figure 3 reports how this formula allows fitting the real diastolic BP values. The top pane describes the behaviour over the train set, the middle pane that over the test set, and the bottom pane refers to the validation set.

For the diastolic pressure the results over the test set, never learned by the GP algorithm, yield an RMSE value of 6.66. In this case the approximation of any actual diastolic blood pressure value with its corresponding computed value over previously unseen data is even better than that for the systolic case, since their difference is now equal to $\pm\sqrt{6.66} = \pm 2.58$ mmHg.

Summarizing the results from these preliminary experiments, PPG values are very important to indirectly estimate BP values.

Fig. 3. Results for the diastolic blood pressure.

The comparison of these results against those achieved in our previous paper [7], in which both PPG and HRV values were used to evaluate blood pressure values, is very interesting. In fact, in that paper slightly lower RMSE values were achieved on both systolic and diastolic values, leading to approximations of ± 1.83 mmHg and ± 1.63 mmHg respectively. Nonetheless, to obtain those approximations we had to use one PPG sensor and one ECG sensor. Here instead, the approximations are a bit higher, i.e. ± 2.91 mmHg and ± 2.58 mmHg, but to obtain these approximate values we need just one PPG sensor. This makes the approach much easier, less invasive, and cheaper.

4 Conclusions and Future Work

This paper has tested the hypothesis that a nonlinear relationship exists between PPG and BP values. Genetic Programming (GP) is well suited to find the relationship between PPG and BP, because it automatically evolves the structure of the most suitable explicit mathematical model for a regression task.

Preliminary experiments on a real-world database have been performed. The numerical results achieved have confirmed that this non-linear relationship indeed exists, and GP has been able to find a mathematical model expressing it. This implies that, instead of measuring a patient's BP in an invasive way, both systolic and diastolic BP values could be indirectly measured by applying a wearable wireless PPG sensor to patient's finger and by making use of the results of a regression analysis linking PPG and BP values. For both systolic and diastolic cases this method involves an approximation error of less than 3 mmHg. Although this model could be difficult to understand for medical personnel who always seeks a physiological explanation, it results accurate.

Unfortunately, this study could involve only healthy subjects. As a future work we will enroll also patients with real cardiovascular problems, in order to test and improve the preliminary results shown here.

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