Research Article

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A Proof of Concept for Blood Pressure Monitoring with Differential Pulse Transit Time and Deep Learning.

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ABSTRACT

Background : Many technological instruments are used in modern therapeutic settings to continuously collect patients' physiological data. This is particularly true in critical care settings, where signals from monitoring equipment may need to be considered when making potentially life-saving decisions. Hemodynamic monitoring is crucial for critically ill patients, dialysis patients, and surgical patients. Blood pressure is often measured for the most seriously ill individuals using a catheter, which is an intrusive process with potential side effects. Additionally, blood pressure can be continuously measured utilizing machine learning techniques by employing a variety of noninvasive monitoring techniques. Previous research has discovered a relationship between blood pressure and pulse transit time. In this little essay, In order to provide a first proof of concept for the validity and viability of a method for blood pressure prediction based on constrained Boltzmann machine artificial neural networks, we propose to investigate the viability of developing a data-driven model.

Synopsis and Main Takeaways: By using invasive catheters, blood pressure is typically measured for the sickest patients (dialysis, surgery, critically unwell). As an alternative, non-invasive techniques for its monitoring have also been developed. Machine learning techniques can be used to continuously assess pressure using data from non-invasive measures. In this paper, a first proof of concept for the validity and feasibility of a blood pressure prediction approach is shown using a constrained Boltzmann machine artificial neural network.

INTRODUCTION

Hemodynamic monitoring is crucial for critically ill patients, dialysis patients, and surgical patients. Blood pressure (BP) is typically measured for the most seriously ill patients via a catheter placed in a peripheral artery, most frequently.

A contribution from the September 28, 2018, University Hospital of Bellvitge, L'Hospitalet de Llobregat, Barcelona, Spain, during the 2nd meeting of "Science for Dialysis."mostly in the femoral or radial arteries, and less commonly in the pedal and iliac arteries. An intrusive operation like arterial cannulation carries a risk of side effects including infection or thrombosis, which can lead to higher death rates and expenses [1].

Numerous techniques can be used to noninvasively monitor blood pressure. Traditionally, the auscultatory method—which uses the sound of the brachial artery pulse when an arm cuff is deflated—has been used to measure blood pressure. The most popular approach for automated medical devices is oscillometric [2]. An inflatable cuff with a pressure sensor inside is also used in this technique. Additional techniques include arterial tonometry [3], which involves positioning a tonometer perpendicular to an artery—typically the radial artery—and most photoplethysmography (PPG) techniques, which also involve inserting a cuff into one or both fingers to measure blood volume (BV). This method uses oscillometry to determine transmural pressure [2]. Using a servomechanism, the cuff pressure is continuously adjusted to maintain this BV during a cardiac cycle. Thus, the force exerted to assert that BV and BP must be equal.

As a result, the majority of BP testing techniques available for clinical practice require the use of a cuff, which can be difficult and uncomfortable in some situations (such as volume clamping). Furthermore, cuff-based techniques have been linked to oversimplifying systolic blood pressure (SBP) and determination of diastolic blood pressure (DBP), particularly in patients who are obese and when an arrhythmia is present [4, 5]. Other noninvasive blood pressure monitoring approaches take advantage of the correlation between arterial pressure (ART) and PPG signals by applying machine learning algorithms. For instance, a data-driven model developed with deep learning is proposed by Ruiz-Rodríguez et al. [6] for the ongoing assessment of BP. However, the respiratory variability of the ART signal meant that this approach was unable to

The American Journal of Kidney Diseases

produce the accuracy needed for clinical use.

It is known that blood pressure and pulse transit time (PTT) are connected [2]. The PTT is defined as the amount of time it takes for a pressure pulse to pass through a section of an artery. The PTT [7] between a finger PPG signal and an arterial line placed in the radial artery is depicted in Figure 1. Many models have been presented to examine the relationship between PTT and BP, which has been the subject of decades of research. Mukkamala et al.'s [2] summary of the models that are available is excellent. Based on the available literature, the following broad conclusions can be made regarding the evaluation of BP from PTT:1. A cuff must be used for calibration on all PTT models.

2. The majority of PTT models use a regression model to evaluate BP, using one of the following inputs:

• 1/PTT
• PTT
• log(PTT)
• 1/(PTT – K)2

In this brief paper, we suggest investigating the viability of putting into practice a data-driven model starting with a calibration. and PTT. The approach presented in Ruiz-Rodríguez et al. [6], which makes use of a significant ANN property, is the foundation of the proposed data-driven model. According to this feature, ANNs can be viewed as universal approximators from a mathematical perspective. According to the universal approximation theorem, assuming reasonable activation function assumptions, a feed-forward network with a single layer and a finite number of neurons can approximate continuous functions on compact subsets. This theorem suggests, in layman's terms, that, with the right parameters, basic neural networks may represent a broad range of functions. The fact that the Navier-Stokes equation, which is unsolvable in general, is strongly related to BP inference makes this property especially pertinent to the current issue. In fact, there is still work to be done in the field of mathematics to solve this equation. Because the commonly employed linear regression models are unable to handle the nonlinear nature of BP inference, neural networks are a better fit for the current situation.

The restricted Boltzmann machine (RBM) will also be the primary component of our regression model in this work. The RBM is the most straightforward unit from which to create deep learning algorithms, and there are highly effective methods for employing these RBMs to train deep architectures. This is the reasoning behind its use.

METHODS

Dataset Description

The MIMIC II [8] database was gathered from Boston's Beth Israel Deaconess Medical Center (BIDMC) during a 17-year period starting in 2001 as a result of a grant from the Bioengineering Research Partnership (BRP). The goal of the project, which was formally established in 2003, was to develop and evaluate advanced intensive care unit patient monitoring systems that would significantly improve the effectiveness, precision, and timeliness of clinical decision making in intensive care. The team included members from MIT, industry (Philips Medical Systems), and clinical medicine (BIDMC). As all data were de-identified and the study had no bearing on clinical care, the need for specific patient consent was dropped.

We obtained the ART, ECG, and PPG records for 250 distinct patients in December 2015 by gaining access to the MIMIC II database for this proof of concept. Every biological signal was captured at 125 samples per second. Biomedical signals were divided into 5-s frames, with just the first frame's calibration from the ART signal. Upon eliminating noise and movement anomalies, we were left with a dataset of 35,188 frames.

Validation Methodology

Our suggested method has been validated using the IEEE 1708-2014 standard for wearable, wireless blood pressure monitoring devices. The validation is split into two phases according to this standard. At least 20 patients are recruited in the first phase, and at least 25 more patients must be recruited in the second phase.

Three stages make up the primary validation procedure: a static test, a test with a blood pressure change from the calibration point, and a test after a predetermined amount of time after calibration. stage I According to the standard, 20% of the recordings and patients for validation must be in one of the following categories: prehypertension (SBP between 80 and 89 mm Hg and DBP between 120 and 139 mm Hg), normal range (SBP <120 mm Hg and DBP <80 mm Hg), or Stages 1 and 2 of hypertension are defined as SBP between 140 and 160 mm Hg and DBP between 90 and 100 mm Hg and SBP > 160 mm Hg and DBP > 100 mm Hg, respectively. Our dataset has been scaled appropriately to meet this requirement. It is also crucial to highlight that, in our situation, there is no cuff-based calibration. Because of this, we have used the BP values derived from the ART signal for both calibration and reference.

Data-Driven Model and Analysis Techniques

The PTT calculated from the QRS complex of the first lead of the ECG recording and the PPG signal using the foot-to-foot algorithm described in Gaddum et al. [7] as inputs for our proposed model are defined as the delay between the waveform valleys at early systole. Following this preprocessing, 25,150 frames from the dataset were used to train an RBM ANN with an architecture made up of three layers—one input layer, two hidden layers, and ten units (RBMs) for each layer—in order to extract the BP values from our PTT inputs.

The remaining frames are set aside for experimentation. The hyperparameter known as the learning rate, which determines how much we can alter the network's weights, was set at 0.001 for the hidden units and 0.002 for the rest. It is crucial to remember at this point that low learning rates are required to ensure the learning algorithm's convergence and enhance the final model's capacity for generalization. Pretraining with 10 epochs was employed by all networks, and weight decay and the moment term were also used by our RBMs.

RESULTS

As per the IEEE 1708-2014 standard, the mean absolute difference (MAD) has been utilized to assess accuracy. Specifically, where yi is the average of the two adjacent reference BP measurements made before and after the device measurement [8], pi is the test device measurement of BP, and n is the data size. The data distributions utilized in the validation process to determine the MAD for DBP and SBP are shown in Figure 2. The findings of our model are compiled in Tables 1 and 2, which also include the IEEE standard grading for our suggested model and three state-of-the-art regression models that use PTT, 1/PTT, and log(PTT) as inputs.

DISCUSSION AND CONCLUSION

In this brief study, we examined the feasibility of combining a data-driven model created with RBMs with a noninvasive algorithm for BP assessment. Our method's first phase validation reveals a marginal improvement over the most advanced techniques based on regression models over PTT. The performance of our regression model declines as the measurement window moves away from the calibration point, as predicted. We had to assess in our instance six minutes following calibration. We believe that the application of these systems in an actual clinical context is obviously limited by this decline in performance.

Another drawback of our research is that, in accordance with the IEEE standard, we were forced to use the BP data obtained from an arterial line as a reference rather than the noninvasive cuff BP monitoring. On the other hand, we also think that the results shown here are less optimistic than they would have been had a cuff. As previously mentioned, cuff-based blood pressure readings have the tendency to exaggerate dilation and underestimate systolic blood pressure. Last but not least, a word of warning.

As a further step, and given the encouraging outcomes of this initial review phase, we suggest assessing our system's ability to follow abrupt changes in blood pressure over a broader population, as needed by the IEEE standard. To further enhance the final system's tracking capabilities, we may also attempt to apply a regression model over a recurrent neural network in this evaluation.

Statement os Ethics : Since the MIMIC II trial had no effect on clinical care and all data were de-identified, the requirement for specific patient permission was eliminated.

Disclosure Statement : The authors affirm that they have no competing interests in seeing this research published.

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