HOW DEEP LEARNING REVOLUTIONIZING MOBILE AUTOMATIC BLOOD PRESSURE MONITORING

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The Covid-19 pandemic has directly affected thousands of lives. The longer-term effects of COVID-19 are already beginning to emerge: the behavioral health toll of anxiety and depression related to the virus itself, which leads to changing our lifestyle to the new normal. Even though Covid-19 became the number one cause of death in the US several times, we actually faced a long global health burden of cardiovascular diseases (CVDs). CVDs have been a worldwide number one killer that kills more people than Covid-19 and, in ordinary years, more than all other infectious diseases accumulated. In 2600-2700 BCE, during the reign of the Yellow Emperor of China, the wellness of human vital organs was used to be assessed by the pulse. The so-called 'hard pulse disease' has been stated as one of the heart conditions where the pulse hardens due to excessive salt intake in food. People diagnosed with this disease were treated with venesection and bleeding by leeches until 1733 when the term blood pressure (BP) was discovered, and the following pathology of disease related to it embarked on the clinicians' interest [1]. In the modern era, the term hard pulse disease is mainly known as hypertension or high blood pressure. It is a leading preventable risk factor for premature death and disabilities caused by CVDs. BP dynamics are affected by diets, activities, emotional states, and the use of BP-lowering medication. Changes in some of these factors, such as increasing BMI and stress load, can elevate the BP; in contrast, medication and changes in lifestyle may reduce the raised BP. Though hypertension can be prevented, thus far, people are still doing terribly on BP control worldwide, especially in low-and middle-income countries (see Fig. 1) [2]. Even the awareness of having high BP is less than half the time of the total sufferer. This escalates the number of researchers in developing a comfortable continuous non-invasive BP (CNIBP) measurement system for users.

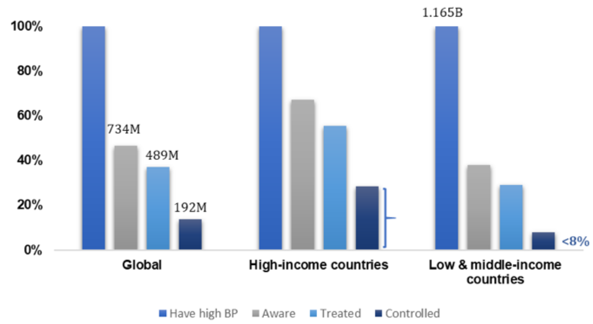

Fig. 1 Most people with hypertension worldwide do not have it under control.

BP Measurement Devices

The invasive catheter system has been considered as the clinical gold standard for measuring continuous BP. This system is performed by physicians or specialized nurses for accurate BP monitoring in intensive care units (ICU). On the other hand, this method is prone to infection when the catheter insertion is performed. Non-invasive cuff-based sphygmomanometer can be an alternative method, which is also recommended for home BP monitoring. Although users can do self-measurement, users have to follow a relatively strict measuring protocol to ensure the values predicted are accurate. The majority (81.4%) of the 914 tested sphygmomanometers exhibited a measuring error that fell within the presently recommended tolerance of ± 3 mmHg. Another drawback is that this device does not allow continuous measurement and the procedure requires time. Both invasive and cuff-based methods are impractical, intermittent, and uncomfortable for patients. Thus, CNIBP systems are expected to fuse the advantages of the two existing methods.

Machine learning-based CNIBP Systems

Several approaches have been proposed, and the pulse transit time (PTT) feature is first utilized. It is often found to have an inverse proportional relationship with BP. By definition, PTT is the travel time between the aortic valve opening and the arrival of the blood flow to the distal location, which can be derived by measuring the time difference between the pulse wave information detected by two sensors apart. There have been a few sensors related to PTT assessment, being investigated in [3]. Based on the heaps of use in literature, the most notable PTT assessment is derived by calculating the time delay between the R peak of the electrocardiogram (ECG) signal to the maximum slope of the (PPG) signal.

At the same time, machine learning regression models, i.e. regression tree, random forest, support vector machine (SVM), help to predict the BP by combining PTT and other related features derived from ECG or PPG signals [4, 5]. Nevertheless, for the overall performance, the prediction error can even be significantly reduced using deep learning methods. Deep learning has a better ability to adapt to represent hierarchical features within multiple layers. We have proven the effectiveness of deep learning techniques compared to some machine learning algorithms in [6]. We proposed a deep long short-term memory (LSTM) model to predict SBP and DBP values from seven features including PTT, heart rate, and the PPG physiology-related information. The real-time demo of this model can be seen in Fig. 2.

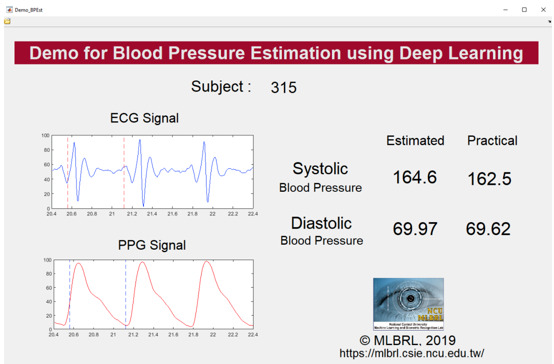

Fig. 1 Our real-time demo program

Deep Learning-based CNIBP Systems using PPG signal only

To accomplish mobile CNIBP systems is a challenging task. Although PPG sensors have been widely used in wearable devices, ECG sensors are still exclusively available in wearable devices. Furthermore, signal retrieval and its preprocessing are the other tricky part. Signals acquired from smartwatches commonly appear quite different from signals acquired from clinical devices due to the very small frequency rate and different kinds of noise that might exist. Thus, a different preprocessing procedure needs to be conducted. To overcome the impracticality of using two separate sensors, most CNIBP system developments are focusing on using

PPG signals only to predict BP. Our initial approach [7] uses a deep neural network (DNN) and 32 selected features from the PPG signal only, illustrated in Fig. 3. Our network architecture contains four hidden layers, denoted as H1, ..., H4. The numbers of neurons for H1, H2, H3, and H4 are 2048, 4096, 8192, and 2048, respectively. The first layer contains 32 neurons, corresponding to the number of our features. The last layer includes two neurons for SBP prediction and DBP prediction.

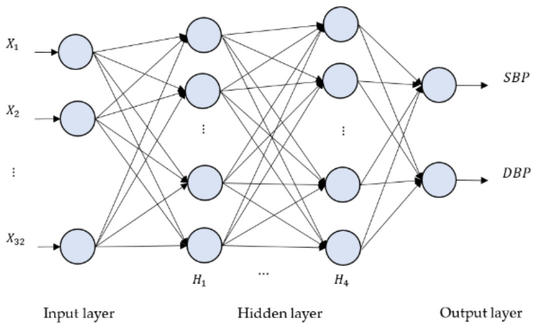

Fig. 2 The deep neural network (DNN) architecture

We decided to adopt the fully connected neural network as our regressor since it is easier to be implemented in wearable devices. The model structure is clean and easier to understand compared to LSTM, which enables software engineers to transfer and deploy the code to wearable devices. Our DNN model achieved a mean absolute error of 3.21 mmHg and 2.23 mmHg for SBP and DBP prediction, respectively.

Commonly, a PPG waveform mainly consists of four distinctive features, namely foot, systolic peak, dicrotic notch, and diastolic peak, as shown in Figure 1. The PPG waveform is quite simple and straightforward but sometimes is not informative. Frequently, the subject's age affects the distinctiveness of the features, such as dicrotic notch, which is usually hard to detect in older subjects, illustrated in Fig. 4. Therefore, features based on dicrotic notch may not be available at all times. Accordingly, we began to focus on developing featureless-based BP estimation.

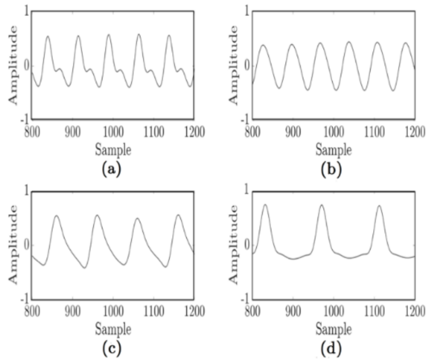

Fig. 4 Waveform variations of PPG waveform including (a) PPG with distinct features, (b) and (c) PPG with indistinct and almost nonexistence dicrotic notch and (d) invisible dicrotic notch with diastolic duration decays faster than the others

Convolutional Neural Network (CNN) is the state-of-the-art of automatic feature extraction while LSTM is an effective choice for analyzing time series data with an ability to handle long sequential data. We proposed a two-hierarchical model consisting of one-dimensional CNN combined with BiLSTM [8]. The lower hierarchy carries out the automatic feature extraction, and the upper learns the temporal relation between the features resulting from the lower part, as illustrated in Fig. 5.

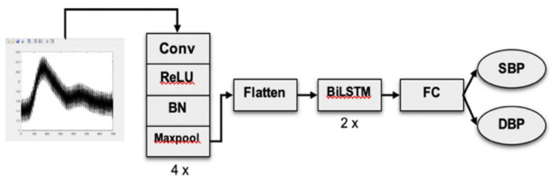

Fig. 5 The 1D CNN-BiLSTM network architecture

Although it did not outperform our DNN model in BP prediction, we believe that in the future, "end-to-end" training, which needs no prior domain knowledge in the loop, will become more popular as the amount of data and computational resources increase. The transition from "feature-based" to "feature-less" signal processing will be a paradigm shift in the biomedical signal processing domain that can also save a lot of training time.

We also proposed a featureless-based model, that not only predicts the SBP and DBP solely but also has the strong learning ability to estimate the whole shape of the arterial blood pressure (ABP) signal [9]. The input of the proposed model is a raw PPG signal along with its derivatives, instead of the hand-crafted feature of the PPG. This model is unimodal and consists of an LSTM-based autoencoder. Furthermore, we applied transfer learning by first training our autoencoder to reconstruct the PPG waveform input. Then, we freeze the encoding part and only let the next part be trained for constructing the ABP waveform afterward. Taking this application can help our network to learn the intermediate waveform representations explicitly. The training flow of our model is illustrated in Fig. 6

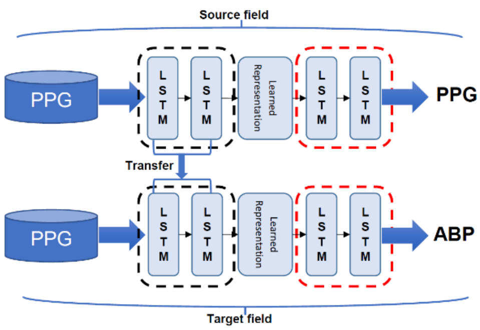

Fig. 6 LSTM-autoencoder training flow. The black dashed-box indicates an encoder, and the red dashed-box indicates a decoder.

The model provides a reasonably accurate and promising result over many subjects being examined, with a mean absolute error of 4.05 mmHg and 2.41 mmHg for SBP and DBP prediction, respectively. Fig. 7 shows the ABP sequence prediction result using the transfer learning method, which has a high resemblance to the observed sequence obtained from the source dataset. In this sense, an LSTM-based autoencoder can perceive the PPG signal information and translate it to the corresponding ABP signal.

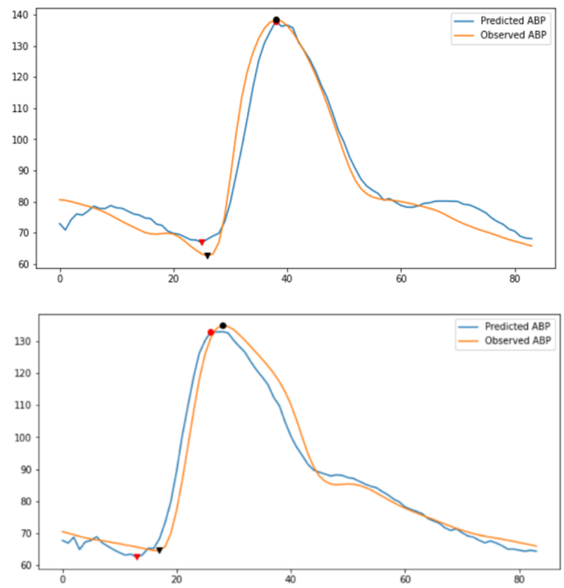

Fig. 3 Examples of ABP prediction results from the proposed model. The circle marks indicate SBP, and the triangle marks indicate DBP.

BPEst Application

Fig. 4 Snapshot of BPEst application for connecting the device with the smartwatch

We have applied our best model to mobile devices as an alternative to the CNIBP system. The application will start working once the smartphone has been connected to a paired smartwatch that has been installed with the same application, as illustrated in Fig. 8. The connection time is less than one minute and the smartwatch will start its PPG sensor and send the data to the smartphone on the fly. After the smartphone receives the data, the waveform of PPG will be shown on the phone screen, and the prediction process will begin. The prediction result will be shown continuously until the user disconnects the smartwatch or close the app, as shown in Fig. 9. The prediction result will also be displayed on the smartwatch screen with a delay time of less than one second, as shown in Fig. 10. Now, monitoring BP can be performed anywhere and anytime using the technology of deep learning-based mobile BP monitoring system.

Conclusion

Blood pressure control is very important despite being neglected by many people. Monitoring BP regularly can be one effort that could be made. Numerous CINBP system has been developed as deep learning emerges as a robust technology that is extremely beneficial in automatic learning and prediction. We have developed our own deep learning models based on LSTM, DNN, and even CNN. Our best model achieved a similar prediction error with the error tolerance of a sphygmomanometer and applied it to mobile and wearable devices to accomplish a proper mobile BP monitoring system.

Fig. 5 Snapshot of BPEst application showing the SBP and DBP prediction

Fig. 6 Snapshot of BPEst application for the smartwatch side

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