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Abstract

Cuff-less and continuous blood pressure (BP) measurement has recently become an active research area in the field of remote healthcare monitoring. There is a growing demand for automated BP estimation and monitoring for various long-term and chronic conditions. Automated BP monitoring can produce a good amount of rich health data, which increases the chance of early diagnosis and treatments that are critical for a long-term condition such as hypertension and Cardiovascular diseases (CVDs). However, mining and processing this vast amount of data is challenging, which is aimed to address in this research. We employed a continuous wavelet transform (CWT) and a deep convolutional neural network (CNN) to estimate the BP. The electrocardiogram (ECG), photoplethysmography (PPG) and arterial blood pressure (ABP) signals were extracted from the online Medical Information Mart for Intensive Care (MIMIC III) database. The scalogram of each signal was created and used for training and testing our proposed CNN model that can implicitly learn to extract the descriptive features from the training data. This study achieved a promising BP estimation approach has been achieved without employing engineered feature extraction that is comparable with previous works. Experimental results demonstrated a low root mean squere error (RMSE) rate of 3.36 mmHg and a high accuracy of 86.3% for BP estimations. The proposed CNN-based model can be considered as a reliable and feasible approach to estimate BP for continuous remote healthcare monitoring.

Keywords: Blood pressure, Electrocardiogram, Photoplethysmography, Arterial blood pressure, Convolutional neural network, Cuff-less blood pressure.

1. Introduction

Cardiovascular diseases (CVDs) are dysfunctions of the heart and blood vessels which includes hypertension, cardiac arrhythmia, cardiac ischemia, and stroke. CVD is the primary cause of universal death and the leading cause of damage to arteries in organs such as the heart, brain, eyes, and kidneys (Cohuet & Struijker-Boudier, 2006). High blood pressure (BP) or hypertension is the single most crucial adjustable risk factor for CVD and monitoring the arterial blood pressure (ABP) is an efficient way to detect and control the prevalence of the CVD (S Ahmad et al., 2010; Silvani et al., 2008). Moreover, early detection of hypertension could decrease disability, mortality and treatment cost. World health organization (WHO) reported 17.7 million people die from CVDs every year, representing 31% of all deaths worldwide, and this number is on the rise (Forouzanfar et al., 2015).

According to 2015 mortality data, the New Zealand Ministry of Health reported that more New Zealander's are dying from CVDs than cancer, diabetes, and infectious diseases. The statistics show one in seven New Zealander has high BP, which comprises 33% of deaths annually (McLean et al. 2013). The need for daily monitoring of hypertension for those with heart diseases is increasing significantly. At the same time, there is a universal interest in changing from hospital-centred care to individual-centred care (Rutherford, 2010).

High BP is the result of multiple parameters, including various abnormalities in cardiac output, blood vessel wall elasticity, circulation blood volume, peripheral resistance, respiration, and emotional behaviour. Continuous monitoring of systolic, diastolic, and mean BP in addition to observing BP waveform shape can significantly increase the ability of clinicians to manage the evaluation of arterial alterations and determine CVD risk. Many studies have indicated that continuous, cuff-less, ambulatory and self-managing BP monitoring systems can measure patients' BP variations during their activities of daily life (ADL) which can then be used for predicting BP-related risks (Pickering et al., 2006). By collecting ADL and BP variations in individuals at risk of CVD, the assessment (Peralta et al., 2014) of a patient's hypertension state can be improved. The related risk factors can be minimized, with clinicians encouraging patients to adopt both a suitable lifestyle and early medical intervention or treatment (Lim et al., 2012). Several studies proposed various methodologies to continuously monitor cuff-less BP, however, meeting the cuff-based BP devices clinical standard is very challenging.

2. Related Work

Currently, there are two most common methods to measure the non-invasive BP, the auscultatory method and the oscillometric approach. These can only monitor the intermittent BP and may cause discomfort due to using the inflatable cuff. The other available methods such as tonometry and volume clamping are either bulky or more intrusive and are not suitable for this purpose.

Recent continuous BP estimation methods are based on pulse wave velocity (PWV) and pulse transit time (PTT) which show promising results. Most of the commercially available devices such as the FDA-cleared Sotera ViSi Mobile (Goldberg & Levy, 2016) and SOMNOtouch NIBP (Goldberg & Levy, 2016) performs continuous non-invasive BP (cNIBP) monitoring, based on PWV or PTT (Mishra & Thakkar, 2017). However, there are many challenges for the broader clinical applications with perhaps the most severe drawback of such methods being the lack of clinically acceptable accuracy.

Recently, researchers have attempted to estimate the BP by feature engineering the ECG and PPG signal as input (Ding et al., 2015; Visvanathan et al., 2013) and then apply regression methods (Ding et al., 2016), support vector machines (Visvanathan et al., 2013) or neural networks (Kurylyak et al., 2013; Şentürk et al., 2018) to estimated BP as output.

On the other hands, deep learning has shown promising results in biomedical technologies such as risk assessment for hypertension (Rodrigues et al., 2016; Saeki et al., 2015), and echocardiography images analysis (Madani et al., 2018; Van Everdingen et al., 2017). There are a few studies using deep learning techniques to monitor BP continuously.

In (Lee & Chang, 2017) authors applied a deep belief network (DBN)-deep neural network (DNN) to learn the complicated non-linear relationship between artificial feature vectors and the reference BP. The bootstrap technique was used to generate eight artificial features from original oscillometric waveforms. Consequently, a significant number of training samples from artificial features were used to estimate the SBP and DBP. Authors in (Peng Su et al., 2018) evaluate a new deep recurrent neural network (RNN) consisting of multi-layered long short-term memory (LSTM) networks to address the accuracy issue over long-term BP monitoring. Ability to perform perception tasks and automatically learning the relevant features of input required to perform the output task for the regression problem is one of the benefits of deep neural networks (Bersano & Sanson, 2018; Wang et al., 2017).

To the best of our knowledge, no one investigated the use of the CWT and CNN for BP estimation. Therefore, we are proposing a CNN-based architecture to estimate the BP from ECG and PPG signals to fill in such an existing research gap.

3. Proposed Methodology

3.1 Database Used

This study relies on the Multiparameter Intelligent Monitoring in intensive care (MIMIC) database. The MIMIC-III Waveform Database records (Johnson et al., 2016) was used for training and evaluation of our proposed CNN model, due to the wide range of synchronized ECG, PPG, and beat-to-beat BP data available. This database was developed by the Laboratory for Computational Physiology at the Massachusetts Institute of Technology (MIT) and includes vital signs, medications, demographics, laboratory tests, and demographical information associated with around 40,000 patients. The database provides high resolution waveform data recording at 125 Hz and clinical information on patients that hospitalized on the Intensive Care Unit (ICU) since 2001 at the Beth Israel Deaconess Medical Centre. Each waveform record contains numeric data which extracted minute by minute physiologic parameters. All the records have simultaneously documented numeric record, each ECG and PPG waveform has an associated ABP numeric record. Moreover, it contains signals from older adults, people with hypertension and other diseases. For our study, a list of patient IDs with available ECG, PPG and ABP signals were created and their related waveforms were extracted.

3.2 Developed Scalograms

A scalogram is a visual method of representing a continuous wavelet transform (CWT), equivalent to a spectrogram generated using a short time Fourier transform (STFT). The CWT provides superior time and frequency resolution to the STFT effectively by allowing different size analysis windows at different frequencies. This flexibility allows for the generation of a smooth image in both time and scale (analogous to frequency) directions. A visual representation of a wavelet transform, having x-axis for time, y-axis for scale, and z-axis showing coefficient value. The amplitude of the frequency components often shown by varying the colour or intensity of that point, typically, dark blue colours represent the low amplitudes and large-amplitude coefficients are represented by brighter colours. In this study, scalograms were created for all input and output signals, a sample of ECG, and PPG and its corresponding scalograms are illustrated in Figure 1.

In this study, the sample data loads as a four-dimensional (4-D) array. The input is a 94-by-409-by-2-by1437. Where 94 is the height, 409 is the width, 2 is the number of channels (ECG and PPG), and 1437 is the number of RGB images of ECG and PPG digits.

The output is a categorical vector containing the labels for each observation. The images are randomly divided into two groups, one for training and the other one for testing. We used 70% of the images for training, and the remaining 30% was used for the testing.

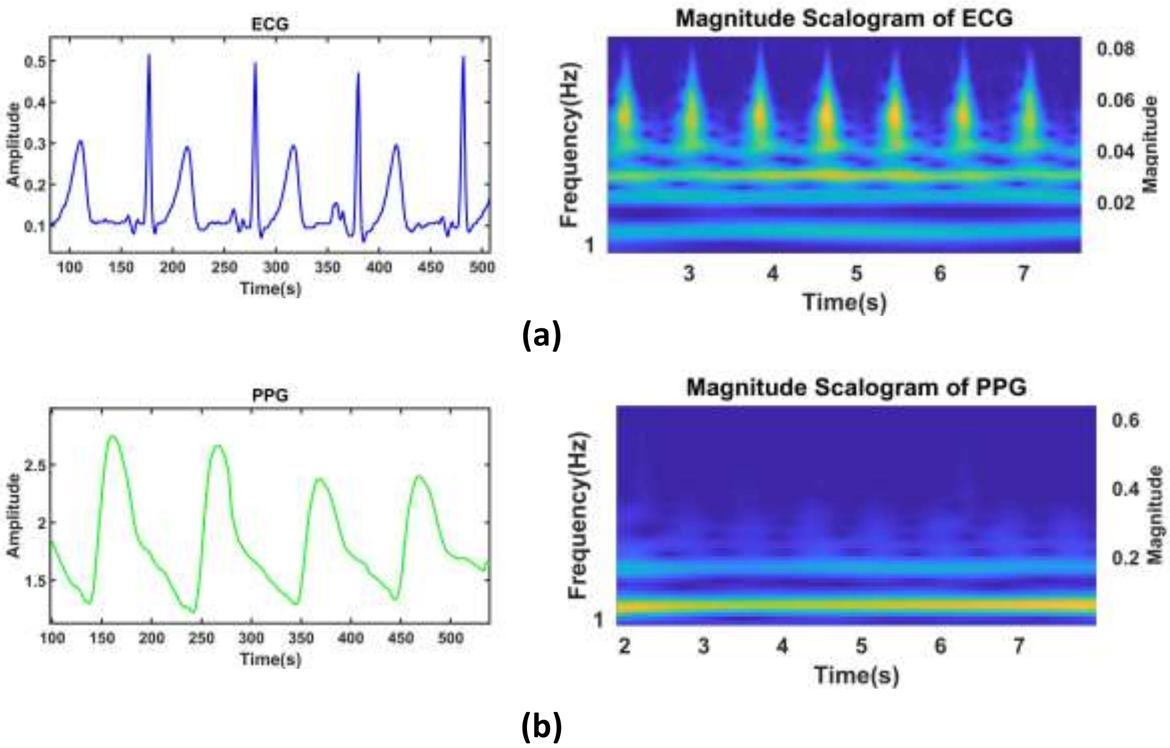

Fig 1: (a) Sample of ECG, (b) PPG and corresponding scalograms

3.3 Convolutional Neural Networks

The convolutional neural network (CNN), is a type of deep neural network (Teramoto et al., 2017) and hierarchical machine learning tool consists of a variety of layers in sequence. A typical model usually is composed of input and output layers, as well as multiple hidden layers. The hidden layers of CNN normally consist of convolutional layers, Rectified linear unit (ReLU) layers, and polling layers, potentially followed by fully connected layers that are particularly powerful for analysis of images.

Normally, convolution is the first layer to extract features from input images and preserves the relationship between pixels by learning image features using small squares of input data. ReLU layers which commonly use after each convolution layer is effectively removed negative input and turns the function returns zero, but for positive input, it turns to the same values. Pooling layers introduce after convolutional layers to progressively reduce the spatial size of the representation, reduce the number of parameters, and the amount of computation in the network. Furthermore, CNNs may also contain fully connected (FC) layers where each neuron of the fully connected layer has full connections to all activations in the previous layer.

3.3.1 Proposed Model Architecture

In this study, to estimate the BP and solve the regression problem, the layers of the network have been created, and a regression layer has been included at the end of the network. The first layer defines the size and type of the input data then generate an image input layer of the same size as the training images. The middle layers of the network define the core architecture of the network, where most of the computation and learning take place. The final layers define the size and type of output data. For regression problems, a fully connected layer has been added at the end of the network.

The proposed network has four convolutional layers (C1, C2, C3, and c4). The input is the scalogram generated from MIMIC III dataset that was sorted as 94×409×2-pixel image. The first convolutional layer has eight kernels of size (3×3×2) with a stride setting of one and same padding. It is followed by batch normalization with eight channels, ReLU, and average pooling with a stride of two and same padding. The second convolutional layer has 16 kernels of size (3×3×8) with a stride of one and same padding. Similarly, followed by batch normalization with 16 channels, ReLU, and average pooling. The third convolutional layer has 32 kernels of size (3×3×16) and the same layer as the previous one with 32 channels batch normalization. The last convolutional layer has 32 kernels of size (3×3×32) and batch normalization with 32 channels followed by ReLU. In order to reduce the overfitting, a dropout layer that performs regularization with a dropout ratio of 20% is used next. Layers are followed by one fully connected layer and regression layer. The details of our architecture for CNN are presented in Figure 2.

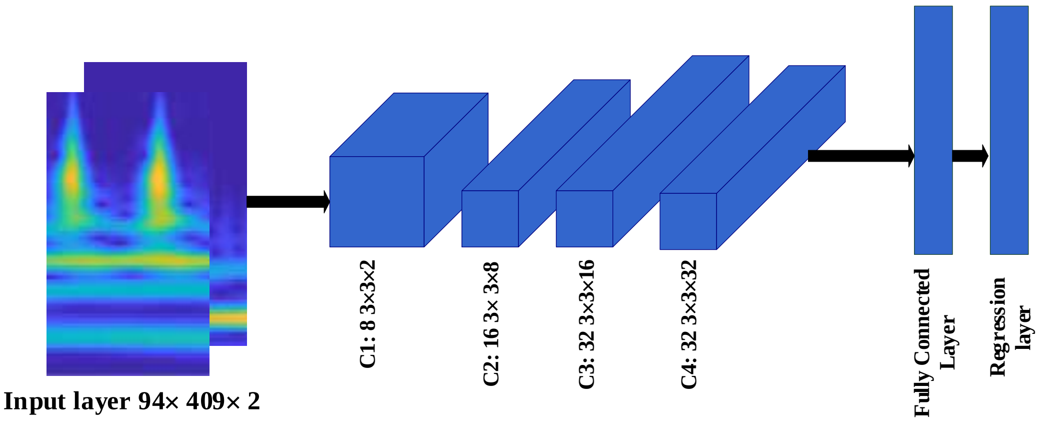

Fig 2: Proposed CNN Architectures for BP Estimation Using Scalogram

4. Experimental Results and Discussion

4.1 Model training

The scalogram images were generated in MATLAB from the MIMIC III waveform database matched subset. For this experiment, 479 patients with available ECG, PPG, and ABP waveforms were selected. All the readings were continuously taken using an invasive method in ICU at a sampling rate of 125 Hz. Although the PPG signals are noisy and the pre-processing step need to be considered, the PPG signals from the MIMIC III database had been highly filtered and further pre-processing was not required.

4.2 Experimental Results

The software environment used for this research was MATLAB R2018b with Intel Core i7-6700 CPU, and CNN model was designed from scratch. The training process conducted with 20 epochs and the average training processes time was approximately 17 minutes. To evaluate our design the percentage of the prediction error between predicted and actual ABP was calculated. The results showed root-mean-square error (RMSE) of 3.3683 mmHg for ABP is within an acceptable error margin that set by the Association for the Advancement of Medical Instrumentation (AAMI) (White et al., 1993). Moreover, we achieved high accuracy of 86.3 % from the estimated ABP measurements compared to the actual measurements. This accuracy achieved by dividing the number of correct predictions by the total number of predictions.

4.3 Comparison and Discussion

We applied the CNN-based model developed from ECG and PPG signals and trained by the scalograms. The ABP was estimated for each patient from CWT and CNN. The achieved results fit within maximal errors of 5 mmHg, which are considered to be acceptable according to the AAMI SP10 standards (White et al., 1993). In addition, our results demonstrated low error and good accuracy, which shows that the proposed model is feasible for continuous BP estimation.

We compared our results with the selected studies from the literature. Table 1, summarizes the comparison results of our model with three studies for BP estimation. The first column shows the BP estimation model used, the second column illustrates the error rate and the last column indicates the use of engineered features.

From the table, it is clear that the proposed CNN-based-BP estimation model gained the least RMSE arte among others, which shows that the proposed model is more accurate. Moreover, the engineered feature extraction method was implemented within these three models, but we did not employ such method as our model learns to extract the related features from ECG and PPG signals. Accordingly, signal pre-processing and the complex feature engineering were not required for the proposed model, which decrease the complexity and improve the processing time. In summary, the proposed CNN model is a more feasible and promising solution for a reliable, efficient, continuous and cuff-less BP monitoring in real-life.

Model	RMSE	Engineered Feature Extraction
• PTT (Pulse Transit Time)(Mishra & Thakkar, 2017)	11	Yes
• SVM (Support Vector Machine) (Şentürk et al., 2018)	6.54	Yes
• RNN(repetitive neural network)- Based Model (Şentürk et al., 2018)	3.63	Yes
• Proposed CNN-based model	3.36	No

Table 1: Comparison of our proposed model with related works

5. Conclusions

In this study, we evaluated the potential of utilising a CNN-based method for continuous and cuff-less BP pressure monitoring using ECG and PPG signals, while maintaining big data in remote healthcare monitoring. The main contribution of this research is using a technique without requiring features extractions system by leveraging the CNN model. The proposed model is suitable and feasible for real-life scenarios where the relevant features are not obvious or difficult to perform. We used 958 waveforms from 479 patients to create scalograms and RGB images using the wavelet-based time-frequency representations. The performance of the network has been evaluated by calculating the RMSE of the estimated and actual ABP with a low error-rate that falls within the acceptable standards range. Moreover, when compared with the other research, the developed model demonstrated higher accuracy and lower error-rate.

While CNN has been showed a good potential to predict the BP in this study, the proposed model can be tricked by a modification of small pixels image. Future work includes further modifications and improvements to the proposed CNN design to achieve a well-stablished algorithms for non-linear complicated relationship between BP and related features. In addition, we would consider to incorporated different database with more samples to improve the CNN performance, aiming to optimise the accuracy of BP estimation and increase the stability of our model.

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