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I declare, I confirm, I certify and I sign that I received substantial, important, line by line peer review with several and substantial comments, important remarks and hints from, at least, 3 Reviewers and the Assistant Editor for my paper: **Signal**

**Quality Classification of Impedance Plethysmogram and  
Ballistocardiogram for Pulse Transit Time Measurement**

with Authors: SHING-HONG LIU, XIN ZHU, TAN-HSU TAN, JIA-JUNG WANG.

I would like to thank all the reviewers for their thoughtful comments and efforts towards improving our manuscript. We revised the manuscript with special attention to the comments that we received from **Three (3)** reviewers who were experts, and specialists in the area of my paper.

I declare, confirm, certify, and sign that WSEAS has checked my paper for possible plagiarism by Turnitin and my paper was found without plagiarism or self-plagiarism by Turnitin. I also declare, confirm, certify, and sign that also that no Associate-Editor, no Editor-in-Chief, and no member of the WSEAS Secretariat forced me in this Journal to add references (citations) to any previous publications of the journal.

I also declare, confirm, certify, and sign that I have made all the changes, modifications, additions, studies, and corrections asked by the reviewers and I have fully complied with their instructions. I also understand that before the publication the 3 (or more than 3) reviewers will check my paper to see if all the changes, modifications, additions, studies, corrections, etc have been done and I authorize the WSEAS to publish my paper or to reject my paper even in the 2nd round of peer review or to continue with an additional round of peer review.

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Please, write additional comments below (take ideas from: <http://wseas.org/main/author-testimonials.html> )

Reviewer 1

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A list of points that appear to deserve to be better clarified in the paper together with some suggestions follows.

1) The authors should revise their paper so that it meets the exact WSEAS format (<https://wseas.com/format.php>).

Response: Many thanks for the reviewer's comment. We modify the format following the WSEAS.

2) The abstract should be thoroughly rewritten. The importance of the work should be pointed out by giving some specific results.

Response: Many thanks for the reviewer's comment. We modify some sentences in the Abstract.

*Abstract:* - Mobile health (mHealth) was developed in the past ten years ago, which used wireless wearable devices to collect the many physiological messages in daily life, regardless of time and place, for some health services including monitoring chronic diseases and reducing the cost of empowering patients and families for handling their daily healthcare. However, the challenge for these measurements is the lower signal quality because users would measure their conditions not on a resting status. Now, the pulse transit time (PTT) being a high relation with the blood pressure has been proposed, which is acquired from the impedance plethysmogram (IPG) and ballistocardiogram (BCG) measured by the weight-fat scale. However, lower signal quality of IPG and BCG, lower accuracy of blood pressure. This study aims to use deep learning techniques to classify the signal quality of **BCG and IPG signals**. The reference PTTs were measured by the electrocardiogram (ECG) and photoplethysmogram (PPG). **The signal quality of each segment was labelled with the error between proposed and reference PTTs. We used three signals, BCG, IPG, and differential IPG, as the input. The proposed one-dimension stacking convolutional neural network and gait recursive unit (1-D CNN+GRU) model to approach the classification. The good performances achieved high accuracy (98.85%), recall (99.4%), precision (94.29%), and F1-score (96.78%). These results show the potential benefit of the signal quality classification for the PTT measurement.**

3) In the introduction section the authors should explain better the problem and analyze other methods and models. A brief description in corresponding studies about mobile health would be useful. More references should be analyzed.

Blood pressure (BP) is the most important physiological parameter for healthcare in the home because it has direct and indirect relations with many chronic diseases, like as hypertension, hyperlipidemia, heart failure, stroke, and kidney disease et al. [5]. According to the World Health Organization's report, people

need to measure their BP at every day and keep their systolic BP lower than 130 mmHg [6]. The commercial and automatic sphygmomanometer uses either auscultatory or oscillometric methods [7]. These methods all use an occlusive cuff wrapping around a user's upper arm to measure the BP. The disadvantage of these methods is uncomfortable when the BP is measured. In the recent years, the cuffless BP measurements have been widely studied [8]. According to the Moens-Korteweg equation, the pulse transit time (PTT) has a high relation with BP [9]. Sharwood-Smith et al. measured the PTT by the ECG and photoplethysmogram (PPG) [10]. They found the relation between the PTT and BP change to be larger than 0.8. Foo et al. used phonocardiography replacing the ECG, and PPG to measure the PTT and estimate the BP [11]. Park et al. used the tonometer measured at the wrist replaced with the PPG, and ECG to evaluate the blood pressure [12]. Liu et al. used an impedance plethysmogram (IPG) measured at the forearm which replaced the PPG, and ECG to measure the PTT and estimate the BP [13]. Liu et al. proposed innovative cuffless BP measuring methods with the ballistocardiogram (BCG) and IPG [14]. The BCG and IPG signals can be measured from a commercial weight-fat scale. However, in these studies, we found a basic problem. The lower quality of signal, the lower accuracy of blood pressure.

The quality of physiological signals generally is labeled by the manual marks of experts [15]. However, the signal quality would depend on the experiences of experts. The rule-based method is to find some characteristics of waveform and classify them whether fitting the normal ranges or not [16]. The disadvantage is how to define the accurate ranges which would be affected by the number of samples. Liu et al. transferred the pulses of PPG and differential PPG (DPPG) to an image and used a convolutional neural network (CNN) for the classification of signal quality [17]. Its advantage was to transfer one-dimension signals to a two-dimension image. Satija et al. showed some methods for signal quality classifications of ECG [18]. We found that the deep learning methods classified the signal quality, which input would be a two-dimensional image. Thus, the complexity of bringing to practice will arise.

4) Can you give us more details and explanations about the research methodology in section 2?

Response: Many thanks for the reviewer's comment. We modify the Methods part.

## 2.1 Experiment Protocol

This study employed 11 males and 6 females who were young and healthy subjects. Their ages were from 22 to 19 years (mean  $\pm$  standard deviation,  $20.2 \pm 1.1$  years), heights were from 186 to 152 cm (mean  $\pm$  standard deviation,  $166.1 \pm 8.0$  cm), and weights were from 115 to 43 kg (mean  $\pm$  standard deviation,  $62.8 \pm 16.1$  kg). The digital sphygmomanometer (HM-7320, Omron, Osaka, Japan) was used to measure the BPs as the reference. The self-made circuit was used to measure Lead I ECG and finger PPG of the left hand.  $PTT_{ECG-PPG}$  was measured from the ECG and PPG which would be the standard PTT. The self-made circuits were used to measure the BCG and IPG signals, and which sensors were at a commercial body weight-fat scale (HBF-371, Omron, Osaka, Japan) [18]. The experiment procedure is mentioned below.

I. ECG, PPG, IPG, and BCG signals were measured for five minutes, and BP was measured once when subjects were standing on the weight-fat scale.

II. Subjects were running on a treadmill to raise the BP until the systolic BP was higher than the 20 mmHg of resting BP.

III. Subjects were standing on the weight-fat scale again, and ECG, PPG, IPG, and BCG signals were measured for six minutes. Their BPs were measured once a minute.

IV. Subjects were measured four times. Each experiment would have a rest for at least a week.

## 2.2 Signal Processing and Segment

The sampling rate was 500 Hz. The 4th-order Butterworth bandpass filter with the 0.5 Hz to 10 Hz bandwidth was used to remove the wandering baseline and high frequency noise. The group delays of all signals group were reduced by an 8th-order all-pass filter. Figure 1 shows these signals, ECG (blue), PPG (red), DPPG (pink), BCG (black), IPG (green), and differential IPG (DIPG, purple). The  $PTT1_{BCG-IPG}$  is the interval between the J wave of BCG and the foot point of IPG, and the  $PTT2_{BCG-IPG}$  is the interval

between the J wave of BCG and the peak point of DIPG. The  $PTT1_{ECG-PPG}$  is the interval between the R wave of ECG and the foot point of PPG, and the  $PTT2_{ECG-PPG}$  is the interval between the R wave of ECG and the peak point of DPPG [14].

We used the error ratio (E) between  $PTT2_{ECG-PPG}$  and  $PTT2_{BCG-IPG}$  of each beat to define the signal quality.

$$E = \frac{PTT2_{ECG-PPG} - PTT2_{BCG-IPG} - Bias}{PTT2_{ECG-PPG}} \times 100\%, \quad (1)$$

where *Bias* is the time delay between ECG and BCG [14]. By the trial and error method, we defined 30% of E as the threshold. When E is below the threshold, the pulse belongs to good quality, this cycle labeling as 1. Otherwise, the cycle is labeled as 0. Figure 2 shows the labels of pulses with the red line. We find that the second pulse belongs to poor quality because the foot of its IPG is at the wrong place. Because the PTT1 and PTT2 were extracted from the BCG, IPG, and DIPG, we used the three signals directly to classify the signal quality.

In the data segment, the window was 1024 points, the overlap was 512 points. In order to reduce the personal affection for the classification of signal quality, the BCG (blue), IPG (red), and DIPG (orange), were normalized, as shown in Fig. 3. **Because one segment has at least two PTTs, the segment was labeled as good or poor quality depending on all pulses in it belonging to all good or poor. The segment would be deleted when the pulses in it had different qualities.** The numbers of good and poor samples were 3938 and 18682, a total of 22,620 samples.

### 2.3 Signal Quality Classifier

A stacking CNN+GRU model was proposed to classify the signal quality as shown in Fig. 4. **The three channels, BCG, IPG, and DIPG signals, are the input. A time-distributed layer is separated into two parts that connect to two one-dimensional CNNs. The CNN has three layers, a maximal pool layer, and a flattened layer. Then, a GRU is connected after the flattening layer. A full connection layer connects with the output layer of the GRU.** In CNN layers, the number of filters is 32, the kernel sizes are 3, 5, and 13, respectively, and the stride is 2. In the maximal pooling layer, the kernel size is 2, and the stride is 2. The activation function is ReLU. The unit number of GRU is set to 1024. The batch size is set to 512, with the control reset gate and update gate using a sigmoid function and the hidden state using a tanh function. **One node is in the output layer, and which activation function is the sigmoid function. One represents the good quality, and zero represents the poor quality.** The threshold of output is 0.5. The dropout in the hidden layer is 0.5. The loss function is the binary Cross-Entropy function, and the Adam optimizer is used, with a learning rate of 0.0001.

Recommendation: The authors need to comply with recommendations.

Reviewer 2

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a) In conclusions section the authors summarize the main points of their study. The authors should explain the contribution of their methodology in comparison to methodologies of other researchers.

Response: Many thanks for reviewer's comment. We modify the texts in Conclusion part.

b) In the conclusion section, the limitations of this study, suggested improvements of this work and future directions should be highlighted.

Response: Many thanks for reviewer's comment. We modify the texts in Conclusion part.

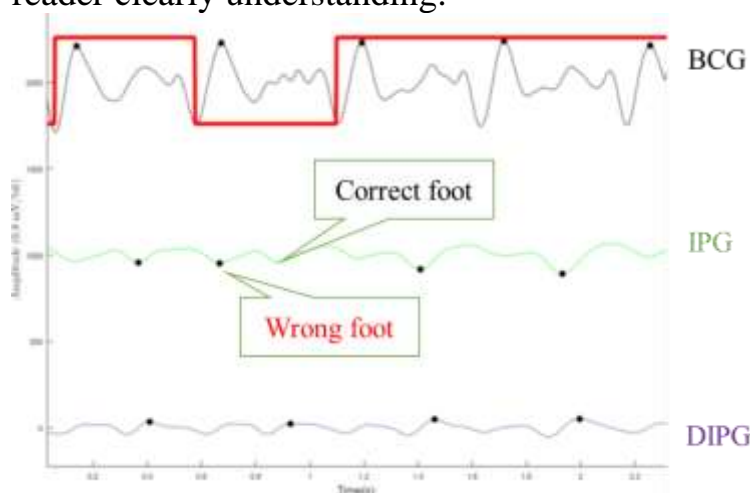
## 5 Conclusion

In the development of mHealth, wireless and wearable devices for monitoring the physiological conditions every day have gotten attention. Now, PTT can be used to estimate the BP, which usually is measured by the ECG and PPG signals when subjects sitting on a chair or lying on the bed. When users are standing on the weight-fat scale to measure the PTT, the signals must have larger artificial motions. In this study, we proposed the stacking CNN+GRU model to classify the signal quality of BCG and IPG signals with the one-dimensional data. The accuracy approached to 98.9%. Thus, it has the potential benefit for BP measurement with the weight-fat scale when users standing on it. Therefore, this method could be applied in the mHealth in the future.

However, the major limitation of this study is that the subjects all were young and healthy people. They stood on the weight-fat scale more stable than the elder. When users have the Parkinson's disease, or use assistive devices for standing, they cannot suit this method.

c) The authors write that 'We find that the second pulse belongs to a poor quality because the foot of its IPG is at the wrong place.' More details should be mentioned.

Response: Many thanks for reviewer's comment. We modify Figure 2 to let the reader clearly understanding.



Signature (insert an image file with a scanned signature or print out the whole page, sign, and scan)

Date: 2024/5/28