Image Based Contactless Blood Pressure Assessment using Pulse Transit Time

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Abstract—Recent years have seen increased attention being given to Blood Pressure (BP) monitoring. Among all kinds of measurements, the monitors based on Pulse Transit Time (PTT) have gained plenty of attention due to its continuous and cuffless features. Additionally, several studies proposed a fancy way to estimate photoplethysmography (PPG) signal simply via a regular webcam. Nevertheless, literatures on issues of integrating these two advanced techniques have emerged on a slowly and scattered way. Furthermore, accuracy of BP prediction model based on PTT is often limited due to the lack of data. To address the above-mentioned problems, we proposed an image-based BP measurement algorithm using k-nearest neighbor and transfer learning results from MIMICII database to real task. The study also introduces newly defined PTT features which are especially suitable for image-based PPG and domain adaptation. Compared with the state-of-the-art algorithm, root mean square error of SBP evaluation has been reduced from 15.08 to 14.02.

I. INTRODUCTION

On the basis of the WHO statistics, hypertension and hypertensive renal disease is estimated to cause 7.5 million deaths, about 12.8% of all deaths per year globally [1]. Hypertension is also commonly regarded as a major cause of cardiovascular diseases (CVDs), which are prime cause of death in the world as well. According to Taiwan Hypertension Society, the number of people exposed to the risk of hypertension has reached up to 6.24 million. Among these patients, only one out of five measures blood pressure (BP) on a weekly basis [2]. Currently, studies pointed out that routinely self-measured BP at home is better than BP measured at hospitals in diagnosing BP-related diseases [3]. On top of that, many environmental factors (e.g. white coat effect) may lead to inaccurate results, as well as subsequent medical diagnosis. Consequently, home BP monitoring has gained increased attention from experts in order to control the progress of heart diseases and hypertension [4].

For most patients, the difficulty in regular home BP measurement may result from the bulky and uncomfortable measuring process. Up to present, commonly used BP monitors (BPM) can be classified into three classes [5]: (a) invasive and continuous, (b) noninvasive and intermittent, and (c) noninvasive and continuous. First, with invasive arterial line, continuous arterial blood pressure (ABP) monitor can measure BP most accurately. Nonetheless, apart from the specific requirement for equipment, the stabbing pain of acupuncture makes this technique difficult to be accepted by patients. Second type of devices frequently utilize auscultation principles or oscillometric techniques (e.g., mercury sphygmomanometer and electronic blood pressure monitor). Although these devices are not invasive and easy to use, an inflatable cuff is necessary, which may give rise to discomfort during assessment. Additionally, devices based on these two principles can only provide intermittent measurement. Lastly, noninvasive and continuous BPMs are commonly developed using the volume clamp method [6] or pulse transit time (PTT) [7]. Volume clamp method was first developed by Penaz, a Czech physiologist, who integrated a finger cuff with built-in photoplethysmograph (PPG) sensor and a pneumatic servo system to estimate continuous BP [6]. Nevertheless, the requirement of a finger cuff may bring about discomfort and the accuracy may be controversial [8].

Recently, to achieve the noninvasive, continuous, and cuffless BP measurement, considerable attention has been paid to the research based on pulse wave velocity (PWV) or its reciprocal, PTT [9-13]. The velocity of arterial pulse propagating through the vessels depends on the arterial wall. Because the arterial wall varies with the arterial pressure, BP can be calculated from PWV or PTT. The original definition of PTT is the time taken by arterial pulse traveling from the heart to a peripheral site. Calculation of PTT conventionally requires R-peak of electrocardiogram (ECG) as the starting timestamp and maximum slope of PPG as the end point [5]. Previous studies found that PTT can as well be calculated from the time interval between two PPG signals measured at different peripheral sites [14, 15]. In spite of the noninvasive and cuffless properties of PTT, patients are required to wear finger clips, chest straps, or gel patches which might bring about skin irritation and discomfort.

To address above-mentioned limitations, a novel contactless technique integrated with image-PPG (iPPG) and PTT has been proposed. The iPPG was first developed by Huelsbusch and Verkruysse [16], who observed PPG signal simply by a regular webcam aimed at
The method is based on the fact that blood volume pulse (BVP) during the cardiac cycle can result in the variation of optical properties on skin. Essentially, the principle employed by iPPG is the same as the one by PPG. Over the past few years, several advanced studies have been proposed to enhance the signal quality of iPPG. In 2015, the feasibility of integrating iPPG and PTT, also named as image-based PTT (iPTT), to estimate BP is first reported by Norihiro Sugita et al. In 2016, Cheol Jeong enhanced the performance using high speed camera at 420 frames per second. Despite the enhanced accuracy, the requirement of high speed camera may make this technique difficult to promote. In this paper, we tried to evaluate BP via iPTT using a regular webcam with a relative lower frame rate (75 fps).

With iPTT or PTT, previous studies exploit different algorithms to model the relationship between iPTT or PTT and BP. Cattivelli F. S. et al. utilized pulse arrival time (PAT), heart rate (HR) and linear regression to evaluate SBP and DBP. Ruiping, Wang et al., took previous BP into consideration and then enhanced the accuracy. Nonetheless, the above-mentioned equation based methods require personal calibration before assessment. The lack of data limits the performance of model. X. R. Ding et al. took advantage of photoplethysmogram intensity ratio (PIR) and PTT to evaluate DBP and PP, showing enhancement upon using PTT only. Nevertheless, PIR is not available owing to varying amplitude of IPPG signals. To achieve the goal of continuous, unobtrusive and contactless BP monitoring, the aim of this paper is therefore twofold: (a) to develop an unobtrusive and contactless BP monitor with newly designed iPTT which is suitable for iPPG. (b) to enhance accuracy of BP estimation with novel k-nearest neighbor (kNN) prediction model. Our results may help to preliminarily investigate the feasibility of transfer learning using database with abundant physiological data, MIMIC II. Moreover, the iPTT method reported here could be beneficial to research attempting to evaluate BP with simply a regular webcam, improving the quality of BP monitoring and diagnosis about BP-related diseases.
The operation principle of proposed system is shown in Figure 1a. A digital camera with 75 frames per second is focused on two regions of interest (ROIs), cheek and palm respectively. The ambient light is regarded as the light source. As described in Figure 1b, the proposed system consists of three signal processing stages, stage I – iPPG Signal Recovery, stage II – Feature point detection and HR/inter-beat interval (IBI)/iPTT Calculation, and stage III – BP estimation using Transfer Learning.

II. METHOD

A. iPPG Signal Recovery

The reason why pulse signal can be captured by a webcam aimed at skin is that a small fraction (<5%) of incident light will be absorbed by the microvascular network which varies with blood volume pulse. In view of [17, 19, 21, 26], while observing the color variation of green channel, we can acquire the highest ac/dc ratio in light reflected from the skin. In consequence, we take the average of green channel in the ROI (20 x 20 pixels) of face and palm as g-traces. Although the quantization noise is preliminary filtered after taking the average of each frame, there are still some other sources of noise (e.g. motion of subject, variation of ambient light). In order to address these noises, we apply a finite impulse response (FIR) bandpass filter (Cut-Off between 45-180 bpm) with hamming window to enhance the quality of pulse signals. The result of filtered signals, iPPG signals, are drawn as Figure 2.

B. Feature Point Detection and HR/IBI/iPTT Calculation

1) Feature Point Detection: First order difference (FOD) is exploited to detect the feature points from iPPG signal.

\[ iPPG'[n] = iPPG[n] - iPPG[n - 1], n \in N \]  

where \( n \) represents the time of each sample and \( iPPG'[n] \) is the differential sequence. Next, we can acquire the sequence of timestamp when the peak or bottom match the following equations.

\[ T_{\text{peak}} = \{ n \mid \frac{1}{2} [\text{sgn}(iPPG'[n]) - \text{sgn}(iPPG'[n - 1])] = -1 \} \]  

\[ T_{\text{bottom}} = \{ n \mid \frac{1}{2} [\text{sgn}(iPPG'[n]) - \text{sgn}(iPPG'[n - 1])] = 1 \} \]  

\[ T_{\text{MaxSlope}} = \{ n \mid \text{arg max}_n (iPPG'[n]) \} \quad \text{and} \quad T_{\text{peak}} > n > T_{\text{bottom}} \]  

where \( T_{\text{peak}}, T_{\text{bottom}}, \) and \( T_{\text{MaxSlope}} \) represent timestamp sequence of crest, trough and maximum slope respectively and sign(•) is the sign function. The result of feature point detection is drawn as Figure 3.

\[ IBI_{\text{peak}}(i) = T_{\text{peak}}(i) - T_{\text{peak}}(i - 1), i \in N \]  

\[ IBI_{\text{bottom}}(i) = T_{\text{bottom}}(i) - T_{\text{bottom}}(i - 1) \]

where \( i \) indicates \( i \)-th pair of IBI, the subscript represents that the instantaneous IBI is calculated from different sequences.

3) HR Estimation: With (5) and (6), we can derive numerous instantaneous IBIs which vary in a large range. To acquire the IBI which best describes the physiological characteristic of iPPG signals in a window, we take the most frequent value in the IBI set (i.e. mode) as real IBI. With the real IBI, HR can be estimated at ease.

\[ HR(\text{bpm}) = \frac{60 \times \text{fps}}{\text{IBI}} \]  

4) iPTT Calculation: Conventionally, PTT is defined as the time consumed by the pulse transiting from proximal (ECG R-peak) to the distal (i.e. peak, bottom or maximum slope point of PPG) arterial sites. To increase the information extracted by two iPPG signals, we extend original one feature of PTT into four features w.r.t. (2), (3) and (4). The definition of proposed iPTT is illustrated in Figure 4 and Table 1.

![Figure 2. Result of g-trace and iPPG](image)

![Figure 3. Result of feature point detection.](image)

![Figure 4. Definition of iPTT.](image)
TABLE 1. DEFINITION OF iPTT.

<table>
<thead>
<tr>
<th>PTT</th>
<th>Starting signal</th>
<th>Starting Time stamp</th>
<th>Stopping Signal</th>
<th>Stopping Time stamp</th>
</tr>
</thead>
<tbody>
<tr>
<td>iPTT1</td>
<td>iPPGsim</td>
<td>Tpeak in previous</td>
<td>Tbottom in</td>
<td>Tpeak in current cycle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>cycle</td>
<td>cycle</td>
<td></td>
</tr>
<tr>
<td>iPTT2</td>
<td>iPPGsim</td>
<td>Tbottom in</td>
<td>Tpeak in</td>
<td>Tbottom in current cycle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>current cycle</td>
<td>current cycle</td>
<td></td>
</tr>
<tr>
<td>iPTT3</td>
<td>iPPGsim</td>
<td>Tink in</td>
<td>Tbottom in</td>
<td>Tpeak in current cycle</td>
</tr>
<tr>
<td></td>
<td></td>
<td>current cycle</td>
<td>current cycle</td>
<td></td>
</tr>
</tbody>
</table>

Since iPTT only depends on consuming time, it will not be influenced by DC noise like different illuminance or distance. In addition, the extended iPTT not only enriches the dimensions of input space but as well enable us to maintain more information after transfer learning.

III. BP ESTIMATION BASED ON TRANSFER LEARNING

In this session, we will discuss how to estimate BP using transfer learning. First, the source domain database, MIMIC II, will be briefly introduced. Next, detail processes of domain adaptation from source to target is reported. Lastly comes to the building of kNN model.

A. MIMIC II Introduction

MIMIC II is one of the largest physiological databases in the world. The data are collected from wide variety of ICUs (surgical, neonatal, or coronary care). In the study, we exploit PPG, ABP, and ECG signals. Among the collected signals, ECG is simply utilized as timestamp for cardiovascular cycle. Because ABP, as well as PPG, varies with blood volume pulse, ABP and PPG signals are regarded as iPPG of face and palm respectively during transfer learning process.

TABLE 2. IRREGULAR RANGE OF BP

<table>
<thead>
<tr>
<th>Irregular SB (mmHg)</th>
<th>Smaller than</th>
<th>Larger than</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBP</td>
<td>80</td>
<td>190</td>
</tr>
<tr>
<td>DBP</td>
<td>50</td>
<td>120</td>
</tr>
</tbody>
</table>

To prune the outliers in collected data, two steps are required before training: (1) to smooth each signal with moving average (125 points). (2) to remove irregular and unacceptable BP value according to Table 2. After the trimming of data, an example set of signals we acquire is illustrated as Figure 5.

B. Domain Adaptation

As illustrated in Figure 6, domain adaptation is competent at learning from the data in which domains of sources and targets are different with same task [27]. There are two steps to adapt and unify the training data from different domains.

1) Unifying the BP distributions via Multi-scale Entropy (MSE): The mismatch of BP distribution between MIMIC II and real world is resulted from the different groups of subjects. The proportion of data related to unhealthy people collected in MIMIC II is much higher than that in real world, resulting in distorted BP and PTT relationship. In light of this concern, MSE [28] is utilized to separate healthy and pathologic groups in the MIMIC II database (tolerance factor r=0.2 or 0.15). As depicted in Figure 7, we can distinguish healthy signals (left) from unhealthy signals (right).

2) Eliminating sample bias and variance via Z-Score: While using MIMIC II database, we cannot obtain where the ABP and PPG signals were measured. Moreover, the PTT can vary widely owing to the different positions of source signals. Although the absolute pulse transit time in two domains are entirely different, shorter PTT still indicates higher BP. That is to say, the consuming time is still meaningful as long as we eliminate the bias of different domains. In light of this, we exploit the Z-score on each feature to eliminate the influence of bias and variance.

\[
iPTT_N = \frac{iPTT - E[iPTT]}{\sqrt{Var[iPTT]}}
\]

where E[•] is the expectation operator, Var[•] is the variance operator, and \(iPTT_N\) is the Z-score of each iPTT feature.

C. kNN Model

Taking \(iPTT_N\) and IBI as input variables, we apply kNN to learn the regression models of SBP and DBP respectively. In this model, k is determined as three and the Euclidean distance is used.
IV. EXPERIMENTAL RESULT

A. Experiment Setup

To our best knowledge, there is no open database which contains both BP signals and videos with palm and face. In consequence, a benchmark database called Camera DB has been built according to following setup. The facial videos were captured by Sony CEJH-15007 in bitmap format with VGA resolution, 75 frame rate and 8-bit depth. The ambient light is regular fluorescent lamp around 400 Lux. As shown in the first photo of Figure 1a, subjects were asked to sit still in front of the webcam with a distance about 70 cm. On the other hand, for each set of experiment, a pair of BP/HR values and a facial video with 40 sec were recorded. The detailed timeline is illustrated in Figure 8.

B. Benchmark Dataset

Following the experiment setup mentioned above, we have collected data from 13 subjects (10 male and 3 female). Each subject conducted the experiment for ten times. As a result, there are total 1300 pairs of data collected. We select ten pairs of data in each 40sec randomly. Eighty percent of data are chosen randomly as training set and the rest are testing set. Table 3 illustrates statistic information of subjects. Moreover, the distribution of the collected dataset is shown in Figure 9. In this dataset, subjects with ideal BP occupy the highest rate, 78.2%. Amount of pre-high BP accounts for 18.8%. Lastly comes the high BP and low BP which respectively take up 1.5%.

C. Result of HR Estimation

The Bland-Altman plot of HR estimation result is shown as Figure 10. The mean absolute error (MAE) achieved 4.35 bpm and root mean square error (RMSE) could achieve 5.15 bpm. This result verifies the effectiveness of HR measurement based on iPPG.

D. Result of BP Estimation

To our best knowledge, there is only one journal article [21] which estimates BP based on video as well. The similarities and differences between proposed algorithm and Jeong’s algorithm are listed in Table 4.

Although Jeong’s algorithm can only predict SBP and trained with Camera DB, we have extended the method with the same transfer learning technique to learn from MIMIC II database. Test with Camera DB, the performances of BP evaluation are listed in Table 5.

Jeong’s algorithm utilizes conventional PTT only; therefore, the performance of benchmark algorithm declines while trained with hybrid database. Using transfer learning with kNN, both DBP and SBP estimation achieve the best performance. In summary, the RMSE of SBP has been reduced from 15.08 to 14.02 with proposed algorithm.
V. CONCLUSION

Integrated with iPPG and the concept of PTT, the paper develops an unobtrusive and contactless BP monitor using a webcam with relative lower frame rate (75 fps). On top of that, newly designed iPTT is proposed for iPPG. With iPTT, proposed method can preliminarily learn kNN model from MIMIC II database using transfer learning. The RMSE of SBP has been reduced to 14.02. Some questions will be exploited in the future. Due to the limitation of experiment, data set for testing is relative small and remains to be built.

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REFERENCES


