Heart Rate Estimation Using Wrist-acquired Photoplethysmography Under Different Types of Daily Life Motion Artifact

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Abstract—Reflective wrist photoplethysmograph (PPG), obtained by a watch or wristband, can provide a natural and unconstrained way for daily life heart rate monitoring. However, reflective wrist PPG often suffers from poor signal quality and various distortions due to daily life motion artifact. In this paper, we analyze the influence of motion artifact on reflective wrist PPG signals, and propose a method to extract reliable heart rate from such distorted PPG signals. The proposed method consists of adaptive filtering, heart rate selection, and motion identification. Experimental results show that our proposed method can generate reliable heart rate values from wrist PPG signals with different types of motion artifact.

I. INTRODUCTION

A. Background

Heart rate is one of the most significant physical signs that are related to human health. Heart rate monitoring are often conducted in the clinical environment where the heart rate of the patient is recorded for doctor to give diagnosis. Monitoring heart rate is not only important for the patient but also beneficial for common people. With the development of the sensor technology, some simple portable devices [1], [2] emerged on the market, enabling people to measure their own heart rate at home. Some products are developed for long-term heart rate monitoring in daily life [3]. Wearable devices for health monitoring would be a trend for telehealth in the future.

Photoplethysmography (PPG) is often used for heart rate measurement [4]. The basic principle of PPG is that different light absorption rate caused by changes of blood flow in the microvascular vessel could be detected by photodiode (PD). According to different traverse path of the received light, PPG could be classified into two different modes: reflected mode and transmitted mode. In the transmitted mode, the light transmits through the tissue, and is received by the PD placed on the opposite side of the body. In the reflected mode, the PD and the light source are located on the same side of the body. PD receives the light reflected by the skin. Compared with reflected mode, transmitted mode can achieve a relatively better signal. Since the light needs to transmit through the tissue, PPG obtained by the transmitted mode can only be measured from limited parts of the body, such as fingertip and earlobe.

B. Related Work

Reflected mode PPG does not have the limited placement problem of the transmitted mode PPG. However, reflected mode is more sensitive to motion artifact and pressure disturbances. Physical activity introduces motion artifact which distorts the PPG signal and makes it harder to extract useful physiological parameters. In [5], the authors designed an earpiece PPG sensor to record the PPG signal from ear. In [6], the authors used forehead reflectance PPG to monitor heart rate. In [7], the authors analyzed the correlation of the PPG and the acceleration signal in frequency domain, and proposed a method to estimate heart rate using the reflective PPG signal acquired from the finger. Their method could produce an acceptable heart rate under motion artifact. However, a fingertip is needed to acquire PPG signal acquired from the finger. Wearing a fingertip will greatly affect the user’s comfort level as many of our daily life activities involve finger movement.

Amongst all the common body parts for PPG measurement, wrist is an ideal site for long-term measurement in our daily life. PPG sensor could be embedded into a watch or a wristband that are worn by the users most naturally. It neither make people look odd (like the sensors on the earlobe or head), nor limit users’ activities (like the sensors on the fingertip). In [8], the authors tried to estimate heart rate from the PPG signals obtained from the wrist during walking. Their method is similar to the method in [7], which compares the acceleration and PPG in frequency domain to eliminate motion artifact.

C. Challenges and Contributions

The major challenge to extract heart rate from the PPG obtained from the wrist is to deal with the motion artifact.
In [9], the author compared the motion artifact effect on different measurement site and reported that PPG signal from the wrist has the worst signal quality in terms of motion artifact compared with finger, upper arm and forearm. Various methods had been proposed to deal with motion artifact in PPG such as singular value decomposition (SVD) [10], independent component analysis (ICA) [11], wavelet decomposition [12], and active noise cancellation [13]. These methods are only applied to the PPG from the finger which had much less motion artifact than the wrist. They may not be able to handle PPG from the wrist with various daily life motion artifact. In recent works [7], [8], acceleration signal has been leveraged to deal with motion artifact in PPG in the frequency domain. The authors only validated their method under running scenario. Whether the proposed method is useful for other types of motion artifact is unknown.

In some preliminary tests we conducted, we gained the following observation. In most motion distorted PPG signal’s spectrum, heart rate component still exists clearly. If we could differentiate heart rate component from the motion artifact, we could extract reliable heart rate from the distorted PPG signal. Our major contribution are three folds:

- We design a novel heart rate detection algorithm which could identify heart rate component under various types of motion artifact.
- We leverage active noise cancellation method to enhance the signal quality for the postprocessing of our algorithm.
- Experimental results show that our proposed method can generate reliable heart rate values from wrist PPG signals with different types of motion artifact.

II. METHODOLOGY

A. Overall Design

Fig. 1 shows the main procedures of our heart rate extraction method. To start with, raw PPG and acceleration signals are captured simultaneously. Raw PPG signals are then fed into the adaptive filter to reduce the noise outside the heart rate frequency band. After that, filtered signals are divided into small segments for Fast Fourier Transform (FFT) to obtain the spectrum of the filtered PPG segments. Meanwhile the acceleration signals go through a walking detection algorithm to identify whether the user is walking. Based on the result from the walking detection algorithm, we will select a heart rate detection algorithm to process the generated filtered PPG spectrum. Finally, we will get the estimated heart rate from the heart rate detection algorithm. Next, we will describe each procedure in detail.

B. Active Noise Cancellation

To enhance the signal quality for postprocessing the algorithm, we leverage the active noise cancellation technique. The

Algorithm 1 Heart Rate Search Algorithm

1: Incoming PPG signals with body status tag.
2: if Body status is non-walking then
3: Update 1s PPG and Conduct 30s FFT.
4: Select 0.83 – 3.33Hz band of spectrum.
5: Let \( P \) denote the set of frequency values in the band, and \( P_{max} \) denote the frequency in \( P \) with the maximum magnitude.
6: \( P_1 = P_{max}, P = P \setminus \{ P_1 \} \).
7: \( P_2 = P_{max}, P = P \setminus \{ P_2 \} \).
8: while \( |P_1 - P_2| < 0.3 \) do
9: \( P_2 = P_{max}, P = P \setminus \{ P_2 \} \).
10: end while
11: \( P_3 = P_{max}, P = P \setminus \{ P_3 \} \).
12: while \( |P_1 - P_3| < 0.3 \) and \( |P_2 - P_3| < 0.3 \) do
13: \( P_3 = P_{max}, P = P \setminus \{ P_3 \} \).
14: end while
15: \( P_i = \arg \min_{p \in \{ P_1, P_2, P_3 \}} |p - P_{i-1}| \).
16: Smooth \( P_i \) as: \( P_i = 2^{-9} P_{i-9} + \sum_{j=0}^{8} P_i - j 2^{-j-1} \).
17: if \( |P_i - P_{i-1}| > 0.5 \) then
18: \( P_i = P_{i-1} \).
19: end if
20: Calculate heart rate \( H_{r_i} \) by \( P_i \).
21: else
22: if Body status is walking then
23: Let \( P_0 \) be the last stable frequency before walking.
24: if Walking duration is fewer than 100s then
25: Record PPG.
26: end if
27: if Walking duration is 100s then
28: Conduct 60s FFT on 40s-100s PPG during walking.
29: Select 1 – 2Hz band of spectrum.
30: \( P_{stable} = P_{max} \).
31: Calculate walking stable heart rate \( H_{r_{i,stable}} \) by \( P_{stable} \) for 40s-100s during walking.
32: Calculate walking rising heart rate \( H_{r_{i,rising}} \) for 0s-40s during walking by linear fitting on \( P_0 \) and \( P_{stable} \).
33: end if
34: if Walking duration is greater than 100s then
35: Update 10s PPG and conduct 60s FFT.
36: Select 1-2Hz band of spectrum.
37: \( P_{stable} = P_{max} \).
38: Calculate walking stable heart rate \( H_{r_{i,stable}} \) by \( P_{stable} \) for these 10s during walking.
39: end if
40: end if
41: end if
raw PPG signals, containing the pulsatile component $S(n)$ and the noise component $N(n)$, are the input of the adaptive filter. To generate the synthetic reference signal in the adaptive filter, we need to remove the pulsatile component $(0.83-4.16\ Hz\ corresponding\ to\ heart\ rate\ 50-250\ beats\ per\ minute\ (bpm))$ from the raw PPG signals’ spectrum. By setting the coefficients of the raw PPG signals’ spectrum to zero and applying inverse Fourier transform to this modified spectrum, we can obtain the synthetic noise reference signal. Another important thing to be determined is the adaptive algorithm of the filter. We choose the widely-used least mean square (LMS) algorithm, which has a high level of stability and a low filter order. The LMS algorithm is used to update the set of coefficients $w(n)$ of the filter. Multiplying the reference signal $R(n)$ with the filter coefficients, we can get the estimated artifact $N'(n)$. The filtered PPG signals $S'(n)$ is generated by subtracting the estimated artifact $N'(n)$ from the original distorted PPG signals. Then the LMS algorithm will use $S'(n)$ as a feedback to update the filter coefficients. The above procedure will run iteratively. The proposed adaptive filter generates $S'(n), N'(n)$ and $w(n)$ as follows:

$$S'(n) = S(n) + N(n) - N'(n)$$  

$$N'(n) = \sum_{i=0}^{L} w_i R(n-i)$$  

\[w_i(n + 1) = w_i(n) + 2\mu S(n)R(n-i), i = 0, 1, 2, ..., L\]

in which $L$ is the filter order. $S(n) + N(n)$ is the original distorted PPG signals. $S'(n)$ is the motion artifact compensated signal, $N'(n)$ is the estimated synthetic noise reference signal and $R(n)$ is the synthetic noise reference signal.

C. Heart Rate Searching Algorithm

The heart rate searching algorithm is the most important component of our method. The periodic pattern of PPG signal is completely distorted when arm is moving. It is impossible for us to calculate the heart rate directly in the time domain. Therefore we divide the filtered PPG signals into small segments and apply the FFT algorithm to obtain the spectrum in order to find the heart rate in the frequency domain.

After the raw PPG signals have been processed through the adaptive filter, the motion artifact that resides outside the heart rate band is reduced. However, some daily life activity will introduce motion artifact with the frequency that overlaps with the heart rate band. Fig. 2(a) shows the spectrum of a 30 seconds clean PPG signals. In the heart rate band, the highest peak corresponds to the heart rate and the other two lower peaks are the harmonics of the heart rate peak. Fig. 2(b) shows the spectrum of a 30 seconds PPG signals during running. We can observe that the motion artifact generates the highest peak at around 1.5 Hz which corresponds to the frequency of swinging arms. The peak at around 3 Hz (two times of the frequency of the highest peak) is the harmonic of the motion artifact. Heart rate peak is preserved but is not the one with the strongest magnitude.

We observed that the PPG signals acquired from vertically placed arm has a very poor signal quality. This makes the heart rate peak in the PPG signals during walking indistinguishable. In Fig. 2(c), the heart rate peak has low magnitude and is drowned in motion artifact and other noises. This problem exists in over half of the data we gathered from different subjects. Thus, we need to treat the PPG signals during walking as a special case, and modify the heart rate searching algorithm in order to provide a reliable heart rate value.

The heart rate searching algorithm is designed to locate the peak corresponding to the heart rate which is mixed with motion artifact. For the walking case, we design a modified version to tackle poor signal quality. Before doing the FFT, We used the 3-axis acceleration signals to identify whether the user is walking. The $x, y, z$ axis acceleration time series are divided into 2 seconds segments, and we will calculate the mean of the samples in each segment. Since walking is a regular motion, the values of the 3-axis acceleration change steadily in three intervals correspondingly. If the mean of the 3-axis acceleration value is within the intervals, then the user activity is classified as walking. If the user activity is not classified as walking, the algorithm will execute the normal procedure. Current heart rate will be calculated using the 30 seconds PPG signals’ spectrum.

Given the spectrum of the filtered PPG signals, we need to first locate all the possible peaks of heart rate. From the gathered data, we observe that, for most of the time during motion, the heart rate peak is within the 3 highest peaks in

Fig. 2. 30s PPG spectra under different conditions: (a) clean PPG from wrist; (b) PPG with 30s motion artifact; (c) PPG during walking.
the heart rate band. Thus, we begin by finding the highest peak $P_1$ and the second highest peak $P_2$. If the distance between $P_2$ and $P_1$ is smaller than the threshold 0.3 Hz, $P_2$ will be discarded, and we will find the next highest peak for $P_2$. The distance threshold is set to avoid selecting peaks that are too close to each other. $P_3$ is the next highest peak after $P_2$, also conforming with the distance condition. After $P_1$, $P_2$, $P_3$ are selected, the one with the shortest distance to the previous selected peak $P_{i-1}$ will be chosen. Because the algorithm update heart rate second by second, within such short period of time, the heart rate is not likely to change dramatically. If we choose the heart rate peak entirely based on $P_{i-1}$, there will be high chance that the selection error will propagate through the following selections. So we smooth $P_i$ by the exponential weighted average of the last 10 seconds’ heart rate, and add a saltation penalty to avoid dramatic heart rate change within a short period of time. Finally, the heart rate is calculate by the frequency of the modified $P_i$.

For the PPG signals during walking, the above algorithm will result in great error because the heart rate peak is usually drown in the motion artifact and other noises. We handle this problem based on the following observation. During regular motion like walking, the heart rate will go through two stages: rising period and stable period. During the rising period, the heart rate will go up rapidly within the first 30 seconds. The duration of rising period varies in different individuals and for different motion intensity. If the motion intensity does not change much, such as walking with a steady velocity, the heart rate will enter a stable period that only has little heart rate variation. As the heart rate changes rapidly during rising period, the energy of heart rate disperses and cannot accumulate a strong magnitude in the spectrum. But in the stable period, heart rate varies little so it can form a distinguishable peak in the spectrum. We differentiate rising period and stable period at the point of 40 seconds during walking. Then we will conduct FFT using the first 60 seconds of PPG during stable period (40 seconds to 100 seconds). We can not locate the heart rate by finding the peak with the shortest distance with the previous peak, because during walking, heart rate is updated less frequently. However, the normal heart rate during walking is between 60-120 bpm. With this knowledge, we can narrow the searching range to 1-2Hz. Also, the major motion artifact caused by walking is mostly less than 1Hz, so the heart rate peak will be the dominant component within the 1-2Hz band. Thus, we will select the highest peak within a 1-2Hz to generate the heart rate in the stable period. The first 60 seconds’ heart rate during stable period will be all set to the same value. After that, heart rate will be updated every 10 seconds using the same strategy. We compromise the updating frequency for a reliable heart rate value. The 40 seconds rising period heart rate will be calculated by using the last heart rate before walking and the first heart rate in the stable period. Since the rising period lasts less than a minute and the heart rate is monotonically increasing, it is sufficient to use the above two values and the linear fitting to reconstruct the heart rate in the rising period.

### III. Experiments

#### A. Materials and Setup

The experimental PPG monitoring system consists of two PPG sensors, two control boards and one 3-axis accelerometer. The PPG sensor we used is called Pulse Sensor, which is a plug-and-play device developed by an open source hardware project. We chose Bluno Nano as the control board, which is designed based on another open source hardware Arduino Uno. It is embedded with BT 4.0 (BLE) module so that the acquired data can be exported via Bluetooth. The accelerometer we used is ADXL345 module from Analog Devices.

Fig. 3 shows the experiment scenario. One Pulse Sensor is attached on the left arm wrist to record the wrist PPG signals. It is connected to the Bluno Nano control board through dupont wire. The accelerometer is also attached on the left wrist next to the Pulse Sensor and connected to the Bluno Nano control board. Another Pulse Sensor is attached on the right hand finger, also connected to the Bluno Nano control board. The other Bluno Nano control board is connected to the laptop. The analog signals acquired by the Pulse Sensor and the accelerometer will be processed by the MCU’s ADC function of the control board with a sampling rate of 125Hz. Then the signals will be transmitted out and received by the Bluno Nano that connected to the laptop. The laptop will record the data and perform offline processing using MATLAB.

**Fig. 3. Experiment scenario**

#### B. Motion Classification

Daily life activities contain various sophisticated motions. We mainly focus on the motions that will affect wrist PPG signals. We classify daily life motions into two categories: arm motion and body motion. The arm motion does not contain the motions from other parts of the body and it only lasts for a shorts period of time (a few seconds). The intensity of arm motion is relatively low compared to body motion. For body motion, we refer to walking and running. Body motion is regular, and usually lasts from tens of seconds to several minutes, or even longer.
We further divide arm motion into six types. For the first three types, the motion of the forearm is only driven by the elbow joint, while the upper arm remains steady.

- Arm motion 1: move the forearm horizontally.
- Arm motion 2: move the forearm up and down.
- Arm motion 3: move the forearm in circle.

The other three types of arm motion involve both forearm and upper arm. The shoulder joint and elbow joint participate simultaneously.

- Arm motion 4: move the arm left and right (similar to wiping window).
- Arm motion 5: move the arm up and down (similar to shaking hand).
- Arm motion 6: move the arm front and back (similar to punching).

In arm motion experiment, we record a seven minutes consecutive PPG signals containing the above six types of arm motion. Each motion is performed for four to six seconds at the start of each minute and repeated once at half the minute. The arm keeps static at the remaining time.

For walking and running experiments, we asked the subjects to walk and run in a comfortable style as they normally do. The duration of the recorded PPG signals is seven minutes long. At the beginning of the second second the subject starts walking or running for three minutes. In the last three minutes, the subject sits statically. As the Bluetooth has a limited transmission range, walking and running is performed in situ.

In total, there are sixteen healthy subjects (6 female 10 male) participating in the preliminary and formal test. We acquired at least five subjects’ data in each of the formal arm motion, walking and running experiments.

IV. Evaluation Results

To generate the correct heart rate as reference, we collected the PPG from right hand’s finger. The finger PPG is acquired with the wrist PPG simultaneously and the right hand is remained motionless during the whole experiment. Heart rate is calculated by a naive heart rate searching algorithm which select the highest peak within the heart rate band from the FFT spectrum. Since the PPG signal collected from finger is clean and with good quality, such naive algorithm is capable of generating a reliable heart rate. Fig. 7 and Fig. 8 show the qualitative and quantitative performance of our proposed method, respectively.

We apply the naive heart rate searching algorithm on the wrist PPG of arm motion and running and compare it to the designed algorithm to illustrate how the motion artifact affect the estimation of heart rate. Fig. 7(a)(b) show the estimated heart rate in the case of arm motion and running respectively. The red curve is the reference heart rate estimated by the finger PPG using the naive algorithm, green curve is heart rate estimated by our proposed algorithm with wrist PPG and blue curve is heart rate estimated by naive algorithm with
wrist PPG. In the arm motion case, the motion artifact is evenly distributed among the whole measurement. We could see large errors (over 20 bpm) occur at several places which last for a few seconds because of the motion artifact caused by arm motion. The heart rate estimated by our proposed algorithm fit the reference heart rate tightly. In the running case, naïve algorithm causes errors continuously during the running period. The heart rate estimated by our proposed algorithm is almost fit with the reference heart rate, only slight error (within 5 bpm) occurs during 90-100s.

In Fig. 3(c) we use the normal procedure of the algorithm to process the walking PPG and compare the estimated heart rate to the result from the walking process part of the algorithm. Red curve is the reference, green curve is the result of the walking process part and the blue curve is the result of the normal part. We could see blue curve is almost part from the reference during the whole walking period. The errors are larger than 20 bpm even though it is generated by the normal heart rate selection part of our proposed algorithm. The reason had stated before, heart rate peak is submerged in the spectrum and the normal selection procedure is bootless. The walking process part of the algorithm compromises the updating frequency for reliability. So we could see the heart rate during the walking period is a straight line which could not reflect the subtle change but the error is acceptable.

The three cases in Fig. 7 represent the general result from our experiment. Under different types of motion, our proposed algorithm could extract heart rate that changed with the reference closely with acceptable error.

The aggregate heart rate error results are showed in the Bland-Altman plots. Fig. 8(a)(b)(c) corresponds to the arm motion, running and walking case. Each plot contains the 1950 pairs of estimated-reference heart rate errors from five different subjects. In the arm motion case, errors are evenly distributed in different heart rate zones, most of the errors are between -7.1 and 5.3 bpm which are in 95% agreement (mean 1.96SD). In running case, the errors in higher heart rate zone (greater than 110 bpm) are larger than those in the lower heart rate zone because higher heart rate appears during the subject is running that causes motion artifact. Some errors are larger than 10 bpm but most of the errors are between -7.6 and +7.7 bpm. Several errors larger than 20 bpm occur. Consider the amount of points plot in the figure, the probability of larger error over 20 bpm is less than 1%. The errors distributed in the walking case are close to those in running case. Some errors larger than 10 bpm occur at the lower part of the figure. Errors within 95% agreement are between -7.6 and +6.6 bpm.

In all cases, most of the errors within 95% reliability are within 10 bpm. Large errors exist but have a probability less than 1%. Thus our proposed algorithm is considered capable of generating an acceptable heart rate under different types of motion artifact. We choose adaptive filter with a synthetic reference to eliminate the noise outside the heart rate band. Our heart rate detection algorithm is able to locate the heart rate peak in the spectrum that is mixed with motion artifact. We also added a special part in the algorithm to deal with the very poor signal quality during walking. Experiments have been carried out to collect PPG signal distorted by different types of motion artifact. The evaluation results showed that the heart rate detection accuracy of the proposed method is acceptable. Our proposed method can be applied to wearable wrist-type PPG systems.

V. CONCLUSION

In this paper, we developed a method which is capable of processing the PPG acquired from wrist with motion artifact. We choose adaptive filter with a synthetic reference to eliminate the noise outside the heart rate band. Our heart rate detection algorithm is able to locate the heart rate peak in the spectrum that is mixed with motion artifact. We also added a special part in the algorithm to deal with the very poor signal quality during walking. Experiments have been carried out to collect PPG signal distorted by different types of motion artifact. The evaluation results showed that the heart rate detection accuracy of the proposed method is acceptable. Our proposed method can be applied to wearable wrist-type PPG systems.