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# Detection of respiratory rhythm from photoplethysmographic signal by adaptive morphological filter

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***Abstract*—An approach using morphological filter technique is proposed to determine the respiratory rhythm from the photoplethysmographic (PPG) signal. As the structuring elements of morphological filter have a decisive effect on the analysis result, in the study the structuring elements are determined by the individual heart rate adaptively. The procedure was tested on a group of healthy subjects. Compared with the reference respiratory signal from the transthoracic impedance measurement, the proposed method is an efficient tool to detect the respiratory rhythm from PPG signal. Furthermore, the low computational complexity of the algorithm may make it easy to be implemented on Microprogrammed Control Units (MCU) for real-time processing. More experimental data is necessary to improve the reliability and robustness of the algorithm.**

## I. Introduction

PHOTOPLETHYSMOGRAPHY (PPG) is an optical technique to detect blood volume changes in the microvascular bed of tissue. The most recognized waveform feature of photoplethysmographic signal is the peripheral pulse ('AC' component), which has the fundamental frequency depending on heart rate. Besides, the pulsatile waveform is superimposed on a slowly varying ('DC') baseline with lower frequency components, which are attributed to respiration, vasomotor activity and vasoconstrictor waves, Traube Hering Mayer (THM) waves and also thermoregulation [1]. Over the last few decades, the PPG technique has been widely used for measuring oxygen saturation, blood pressure and cardiac output in clinical application. Recently, driven by the demand for low cost, simple and portable technology for the primary care and community based clinical settings, there has been a great interest in the research on detecting respiratory rhythm from PPG signal.

The low frequency respiratory-induce intensity variations (RIIV) contained in the PPG signal was discovered by Lindberg in 1992 [2]. It was considered that the RIIV signal includes contribution from the variation in the peripheral circulation caused by respiration. A few methods have been developed to extract RIIV component from PPG signal and to detect the respiration rhythms. Johansson [3] presented an algorithm based on pattern recognition to obtain RIIV from reflection mode PPG measurements and got low error classification rates in the region of 10%. Foo and his co-workers [4] designed zero phase digital filter extraction of the breathing interval in children. Wavelet transformation based algorithms [5], [6] to automatically estimate the respiratory rate were proposed in the recent years. Although most of the methods had good performance, their high complexity is not available for the portable real-time monitor. The low computational complexity algorithms are necessary to speed the realization of multi-parameters monitor including respiratory rhythm based on PPG technique.

Morphological filter is an efficient tool in signal processing by incorporating shape information of the signal. Detection methods based on morphological filter have been used for baseline correction and noise suppression of ECG signal [7], [8], in which open-closing operation with a line structure element was selected as the basic algorithm. Using a morphological filter with proper morphological operation and structuring elements, it is possible to decompose a raw signal into several physical parts. The most advantage of the method is its simple and quick sets computation which may make it easy to be implemented on MCU for real-time processing.

In the study, we propose a method based on morphological filter, which can be used in automatic detection of the respiration rhythm. As a sticking point of morphological filter, the structuring elements are determined adaptively by the heart rate of each individual PPG signal. The other lower frequency components and respiratory part are separated and the main morphological characteristic of the respiration component is retained.

## II. Methods

### A. Subject and Data Acquisition

For the study, 6 healthy volunteers (4 male, 2 female), aged 25 to 36, breathing air, were monitored in an upright sitting position. A probe was attached firmly to the index finger of the right-hand with the optical source directed through the fingernail. In each trial, the volunteers were asked to time their respiration rate in synchronization with an on-screen timer. Three different rate of 6, 12, 18 breaths per minute (0.1Hz, 0.2Hz, 0.3Hz respectively) were required.

A PPG module (180502, Creative, Shenzhen, China, 518054) was used to monitor the probe output in all trials. We used the infrared signal before its data logging and the signal was as "pure" and unprocessed as possible. For each trial, the volunteers had more than 30 seconds initial transient ("settle down") period of the time. After that, 120s of trace were

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recorded. The reference respiratory signals were measured simultaneously by an ECG unit (11010410, Create, Shenzhen, China, 518054).

### *B. Fundamental theory of mathematical morphology*

Mathematical morphology is a set-theoretical approach to digital signal or image analysis based on shape. There are two basic morphological operators: erosion and dilation. Opening and closing are two derived operations defined in terms of erosion and dilation. These operators are described in detail below with corresponding mathematical expressions.

Throughout this section, $s(n)$ denotes a discrete function defined on $S=\{0,1,..N-1\}$ and $B(m)$ , $\{m=0,1,...M-1\}$ is a symmetric structuring element of M points:

Erosion is defined as:

$$(S\Theta B)(n)=\min_{m=0,\dots,M-1}\left\{S\left(n-\frac{M-1}{2}+m\right)-B(m)\right\} \quad (1)$$

where $n=\left\{\frac{M-1}{2},\dots,\ N-\frac{M+1}{2}\right\}$.

Dilation is defined as:

$$(S\oplus B)(n)=\max_{m=0,\dots,M-1}\left\{S\left(n-\frac{M-1}{2}+m\right)+B(m)\right\} \quad (2)$$

where $n=\left\{\frac{M-1}{2},\dots,N-\frac{M+1}{2}\right\}$.

Opening: $S\circ B=S\,\Theta B\oplus B$ (3)

Closing: $S\bullet B=S\oplus B\,\Theta B$ (4)

Opening operation of a data sequence can be taken as sliding a structuring element along the data sequence from beneath and the result is the highest point reached by any part of the structuring element. Similarly, the result of closing operation is the set of lowest points reached by any part of the structuring element.

### *C. Adaptive algorithm to detect respiration rhythm from PPG*

As we mentioned, the PPG waveform contains two components, one attributable to the pulsatile component in the vessels is caused by the heartbeat and gives a rapidly alternating signal ('AC' component) and the other is a slowly varying ('DC') baseline with various lower frequency components. The identification of respiratory features is often masked by other lower frequency artifacts in the PPG signals. The proposed algorithm based on morphological operators provides a solution for the removal of the lower frequency baseline drift and a simple method to detect the respiratory rhythm. The block diagram of the algorithm is shown on Fig. 1.

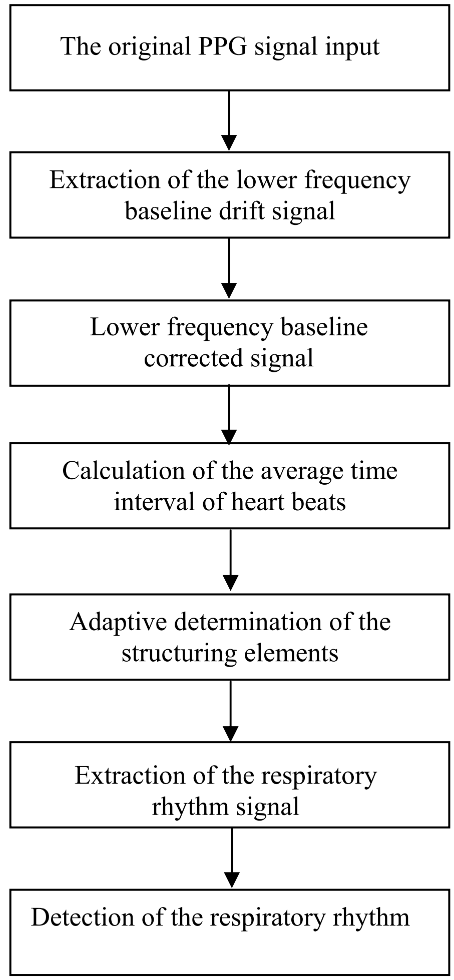


Fig.1. Block diagram of the algorithm

The lower frequency baseline drift extraction is performed as follows:

$$S_U(n)=S_O(n)\bullet B_1(m_1)\circ B_2(m_2)\,, \quad (5)$$

$$S_D(n)=S_O(n)\circ B_1(m_1)\bullet B_2(m_2)\,, \quad (6)$$

$$S_B(n)=\frac{1}{2}\big(S_U(n)+S_D(n)\big), \quad (7)$$

where $S_0(n)$ is the original PPG signal, $S_U(n)$ is the detected upper contour of the PPG signal, $S_D(n)$ is the detected lower contour of the PPG signal and the $S_B(n)$ is the lower frequency baseline drift signal by averaging the upper and lower contours of the PPG signal. The structuring elements $B_1(m_1)$ and $B_2(m_2)$ are line segments with different lengths.

$$B_1(m_1)=0 \quad (m_1=0,1,2,...,M_1)$$

$$B_2(m_2)=0 \quad (m_2=0,1,2,...,M_2)$$

To extract the lower frequency baseline drift, we use both open-closing and closing-opening operation. Statistically, the result of opening-closing operation has lower amplitude than original signal and the result of closing-opening operation has higher amplitude than original signal. So it can retain the peaks or valleys of the signal. And an average weighted combination of open-closing and close-opening is utilized to avoid the amplitude deflection. In this step, we set the lengths of the structuring elements as $M_1 = 500$, $M_2 = 750$.

The correction of the lower frequency baseline is then done by subtracting $S_B(n)$ from the original PPG signal. From the corrected signal, the traditional cross-zero detection method can be used to determine each pulse of the PPG signal. Then the exact average interval of the pulsatile wave can be calculated for each certain period of time, on which the structuring elements are dependent.

Assume the duration of the pulsatile wave is T second. The sampling rate is 500samples/S. The length of the structuring element $B(m)$ should be 500AT, A is a constant coefficient. It means the length of the structure element changes adaptively with the individual heart rate. Then the Respiratory rhythm signal is extracted as follow:

$$S_{Dup}(n) = S_{PPG}(n) \bullet B(m) \circ B(m) \quad (8)$$

Although the respiratory rhythm signal does not reflect the amplitude fluctuation of respiration exactly, the period of respiration can be detected from it. We set a flag for each point of the respiratory rhythm signal. If the value of the current point is not more than the previous, the flag of the point is set to positive one, else to negative one. If the product of the current flag and the previous flag is less than zero, the current point can be taken as the start point of a respiration period. By such method, we can detect the rhythm of the respiration.

## III. Result

18 PPG sequences from 6 subjects each with three different respiration rates were processed by the algorithm. Fig. 2 shows the related waveforms, where Fig.2(a) is the 1 minute original PPG signal measured from subject 3 with 18 respirations per minute; Fig.2(b): the red line is the upper contour of the original PPG signal; Fig.2(c): the red line is the lower contour of the original PPG signal; Fig.2(d): the red line is the lower frequency baseline drift signal by averaging the upper and lower contour of the PPG signal; Fig.2(e) is the baseline corrected signal; Fig.2(f) is the detected respiratory rhythm signal. The waveforms corresponding to the different morphological operations are shown clearly on Fig.2.

From the detected respiratory rhythm signal (Fig.2(f)), we detected 17 respirations in the minute. On the other hand, by the reference signal and also the control rate, during the minute, subject 3 took 18 respirations in practice. One error respiration occurred.

Table 1 contains a summary of the results from the respiratory rhythm detection study for all 6 subjects by the algorithm using the adaptive morphological filter. There are 18 data sequences and total 432 respirations. The algorithm has detected 407 respirations correctly with the detection rate of 94.21%. 25 respirations has been failed to be detected. Table 1 also includes details of the false positive and false negative. The number of the false positive detected is to zero and the percentage of false negative is 5.79%.

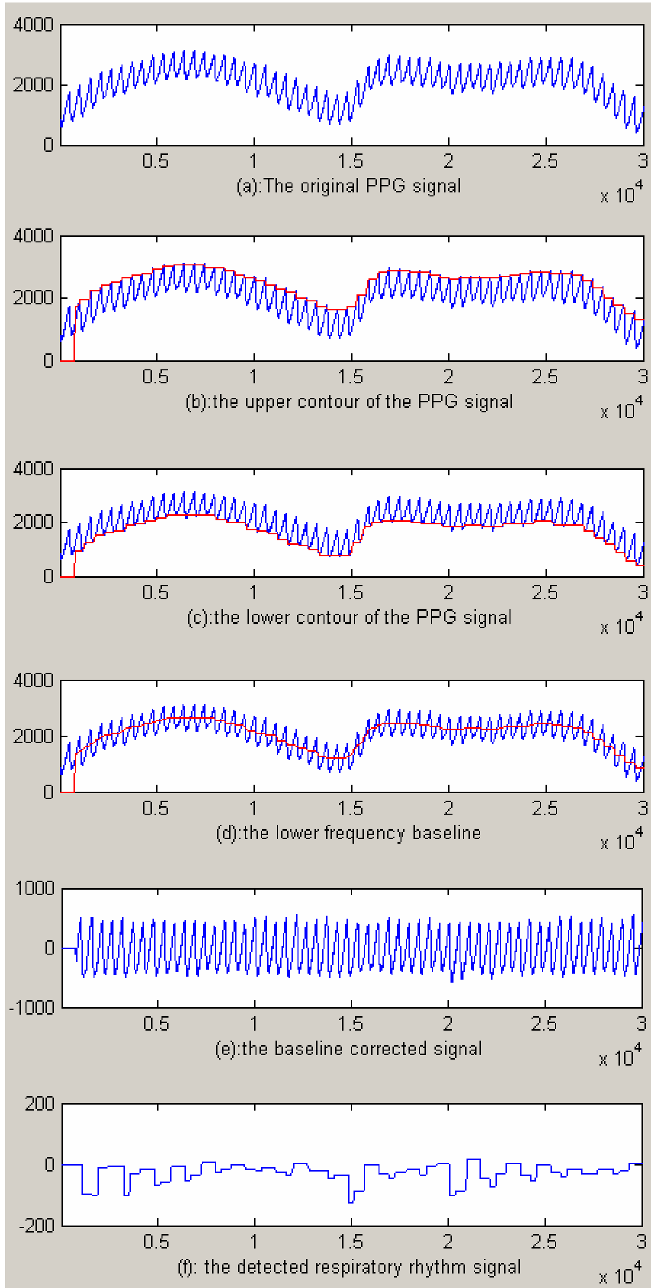


Fig. 2. Waveform related to the algorithm of subject 3

(a) the original PPG signal for one minute
(b) the upper contour of the PPG signal
(c) the lower contour of the PPG signal
(d) the lower frequency baseline
(e) the baseline corrected signal
(f) the estimated respiratory signal

Table 1. Respiration detection results from the reference signal and the estimated respiratory signal

| Volunteer ID | Reference Respiration | Detected Respiration | False Number | False Rate (%) |
|---|---|---|---|---|
| V1 | 12 | 11 | -1 | 8.33 |
| | 24 | 23 | -1 | 4.17 |
| | 36 | 34 | -2 | 5.56 |
| V2 | 12 | 12 | 0 | 0 |
| | 24 | 24 | 0 | 0 |
| | 36 | 33 | -3 | 8.33 |
| V3 | 12 | 12 | 0 | 0 |
| | 24 | 22 | -2 | 8.33 |
| | 36 | 33 | -3 | 8.33 |
| V4 | 12 | 12 | 0 | 0 |
| | 24 | 23 | -1 | 4.17 |
| | 36 | 34 | -2 | 5.56 |
| V5 | 12 | 12 | 0 | 0 |
| | 24 | 22 | -2 | 8.33 |
| | 36 | 34 | -2 | 5.56 |
| V6 | 12 | 11 | -1 | 8.33 |
| | 24 | 22 | -2 | 8.33 |
| | 36 | 33 | -3 | 8.33 |
| Total Detection Rate | | | 407 / 432= 94.21% | |
| False Positives | | | 0 | |
| False Negatives | | | 25/432= 5.79% | |
| Total False Rate | | | 5.79% | |

## IV. Discussion

The experimental results show that our adaptive morphological filter based algorithm had a good performance on detection of individual respiratory rhythm from the PPG signal. As we mentioned in the previous section, morphological operations are made up of addition, subtraction, and logical comparison, especially in our application, only logical comparison being used. So the algorithm is easy to be implemented on micro control units for real-time processing. It is quite well suited for the requirements of the miniaturization of portable monitors.

Due to the characteristic of the morphological operations, at the beginning or the ending of the processed sequence, a short segment may be set to zero. Such phenomenon can be seen clearly in Fig.2 (b), (c), (d). Therefore, the respiration may fail to be detected at the beginning or the ending of the signal sequence. That is the main reason for most of the false negatives in our experiment.

The second possible reason for the error respiration detection is due to the low ratio of the signal to noise. It is obvious that the amplitude of the respiration decreases accordingly when the respiration rate goes up. For the signal with the comparatively low amplitude of respiration, a weak artifact may result the failure of respiration detection. In a word, the performance of the algorithm is dependent on the ratio of signal to noise. Detailed results can be seen in Table 1 that with the respiration rate of 6 times per minute, the maximum false negative is 1, of 12 times per minute, the maximum false negative increases to 2 and of 18 times per minute, the value reaches 3.

For the preliminary study to our algorithm based on morphological filter, the PPG sequences from 6 subjects are limited. More experiments are required to verify the sensitivity, specificity, robustness of the algorithm. However, the experimental result still shows that the adaptive morphological filter seems particularly well suited for detecting respiratory rhythm from PPG sequences.

## V. Conclusion

Respiration monitoring is important in many clinical settings, including critical and neonatal care, sleep study assessment. Continuous monitoring of respiratory rhythms can be done clinically, but requires additional equipment and is obtrusive in nature and labor intensive as well. The PPG technology has been used in a wide range of portable medical devices. Measurement of respiration from the PPG signal would greatly simplify the monitoring of respiration. Using morphological filter to detect respiratory rhythm from the PPG signal is attractive for its special characteristics. Its low computational complexity and good performance on respiration detection make it possible to be implemented in simple, low-cost way. It is envisaged that our technique can lead to wider use of respiration monitoring.

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