Performance Improvement of Pulse Oximetry-Based Respiration Detection by Selective Mode Bandpass Filtering

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Abstract. In this paper, an improved method to detect respirations by pulse oximetry during exercise is proposed. As a method for robust respiration detection, fixed bandpass filtering to block the heart beat signals is commonly utilized. But the fixed bandpass filtering cannot guarantee reasonable performances when the HR(Heart Rate) is varied highly. Therefore, the respiration detection performance is degraded. In the proposed algorithm, the HR information is used to estimate the RR(Respiration Rate). Using the RR, the corresponding bandpass filter(BPF) is selected to detect respiration points. The selection of the passband makes the proposed algorithm possible to guarantee the performance during exercise. Our test results show that the overall estimation error of the proposed algorithm was 20.32% during exercise.

Keywords: pulse oximetry, SpO_2, health care system, biometric signal processing algorithm, respiration detection.

1 Introduction

During aerobic exercise, respiration rate control is essential to increase its effectiveness[1]. That is, the effectiveness can be raised by the respiration rate suitable for a given exercise. On the other side, wrongly trained respiration habits increase the possibility of damage to human organs. In order to investigate respiration efficiency of an exercise, the amount of required oxygen can be directly derived from its load. Besides, the amount of oxygen actually absorbed in the human body is also important. To estimate it, additional sensors and corresponding signal processing from them are indispensable.

Typically, as the method of respiration measurement, the ECG(Electrocardiogram) system is the best in the view of precision[2] [3]. For this reason, it is widely adopted to hospitals or sports research institutes. But, in spite of the advantage, it has several

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critical problems. Its sensor attachment is not convenient, and the cost of maintenance is not affordable to households. These are obstacles to popularize the system as home exercise equipment.

To overcome the problems, pulse oximetry, which is focused on our research, is applied to the respiration detection during exercise. When pulse oximetry is employed to automatic exercise prescription systems, its usage can be stretched from medical monitoring systems to household health care systems. In the sense of usability, the simple snap of a pulse oximeter improves the convenience in sensor attachment and it needs no additional cost for maintenance.

Because pulse oximetry is simple but powerful, related researches and applications have been continuously developed for the last decades. In some cases, it is used for heart beat-related researches, and in the other cases, it is applied to respiration analysis systems[4]. Among them, researches related with respirations are difficult and challenging. But, reliable performances are guaranteed only in the limited conditions like paced respirations or less intensive exercises[5] [6].

In order to detect respirations by pulse oximetry during intensive exercise, the proposed algorithm is concentrated on the robustness in detecting the RR. When the conventional fixed bandpass filtering with the possible RR(0.1~1.4Hz) is simply performed to the SpO_2 signal, unexpected artifacts makes the detection of respirations difficult. Moreover, the conventional method cannot guarantee robust performances because the range of the HR(1.0~2.8Hz) and the RR becomes overlapped during exercise. So, it is difficult to set the passband for respiration. In addition to the problem, artifacts are possibly included into respiration wave due to the broad range of the RR. Consequently, dynamic adjustment of the passband is necessary to the respiration detection.

Our algorithm has following procedure to dynamically adjust the passband. First, heart rates which are less vulnerable by artifacts are measured with SpO_2 signals in the time domain. Next, through frequency analysis, the strongest frequency component among the spectral bins slower than the HR is recognized as the estimated RR. Finally, respiration points are detected after filtering the SpO_2 contour using the BPF based on the estimation. The dynamic adjustment of the passband makes the proposed algorithm cover all possible intensity of exercise.

The paper is organized as follows. Section 2 describes related work. Section 3 deals with pulse oximetry for exercise. From Section 4 to 6, the proposed algorithm is described. The Experiments and the results are presented in Section 7. Finally, the discussion and the conclusion are given in Section 8 and 9.

2 Related Work

The ECG can be used to detect respirations[2] [3]. Among various methods, it must be the most reliable. But, it requires cumbersome electrode attachment to the skin. It also has a problem of disposable electrodes. Wastes and costs occur in the measurement process.

Pulse oximetry is widely used for patient of intensive care units. During paced respiration, respiration can be detected by pulse transit time[5] [7]. Once an inspiration occurs, pulse transit height is recovered to the original magnitude. But, fluctuations or sudden noises in SpO_2 signals disturb using this method to the detection of the RR during exercise.

Pulse oximetry is importantly applied to patients in hospitals to detect HR's. During the HR measurement, removal of artifacts caused by an unfixed clip-type sensor is requested. Most artifacts in SpO_2 signals are due to the loose attachment of a sensor, motion effects and electronic noises, etc[8]. Spectral analyses and the independent component analysis are employed to reduce those artifacts and extract HR's[4] [8].

Without the swing of the sensor and the motion of the body, a fixed BPF which has the passband near the RR can be useful to block the artifacts and heart beat components in SpO_2 signals[9]. But, the HR is varied highly during exercise. So, the fixed BPF method cannot show a stable performance.

3 Pulse Oximetry for Exercises

3.1 Necessity of Dynamic Passband Adjustment

When the intensity of an exercise increases, the oxygen consumption of the human body is increased, and the blood circulation system reacts faster[10] [11] [12]. Subsequently, heart beat and respiration components in the SpO_2 signal have higher frequencies[13] [14]. During exercise, the frequency range of HR's and RR's are 1.0~2.8Hz and 0.1~1.4Hz, respectively.

As a result of the higher intensity in the SpO_2 signal during exercise, the range of the HR and the RR become broader and sometimes overlapped. In this case, the BPF which is designed to cope with the whole possible RR range cannot exclude the HR successfully. The error of the HR and the RR is due to the failure of the peak point detection after the bandpass filtering. In order to prevent this kind of failure, the passband should be adjusted dynamically by using the HR information. Moreover, in the case of fixed bandpass filtering, broad range of the passband is disadvantageous to avoid possible artifacts including heart beats.

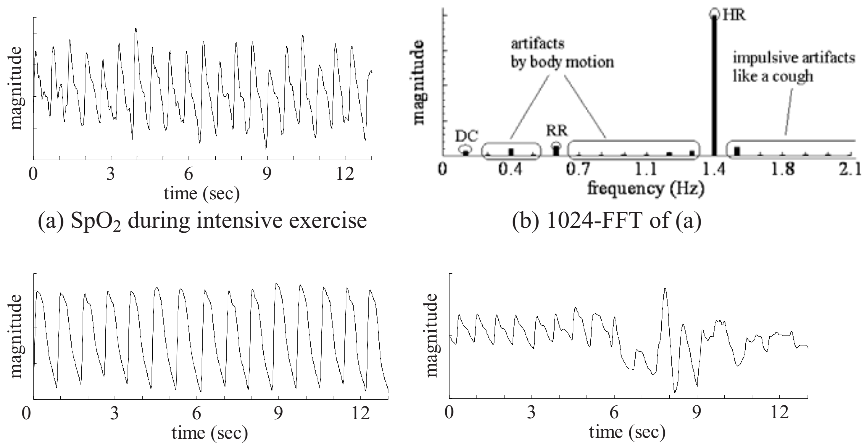
On the other side, in the case of less intensive exercise, the range of RR's is 0.1~0.6 Hz, and that of HR's is 1.0~1.5Hz. Because each range is not overlapped, the necessity of the dynamic adjustment is not issued.

3.2 Internal Respiration and External Respiration

Respirations are classified into the external respiration (mechanical motion of the lung) and the internal respiration(oxygen refreshment of hemoglobin). While the external respiration consists of inspiration and expiration, the internal respiration is the biochemical process of hemoglobin with oxidation-reduction reaction[15]. Because of the difference between these two kinds of respirations, they are not tightly related to each other. That is, in some cases, the oxygen refreshment of hemoglobin may not follow the motion of the lung. They also show less correlation in case a subject is unhealthy.

3.3 Intensities of Exercises and SpO_2 Signals

The proposed algorithm is concentrated on the case that has a distinctive respiration frequency like fig. 1(b). Intensive exercise increases the magnitude of the respiration. When it overcomes the magnitude of artifacts, the proposed algorithm can properly work.



(a) SpO_2 during intensive exercise (b) 1024-FFT of (a)

(c) SpO_2 in supine status (d) distortion by unstable sensor attachment

Fig. 1. Signal characteristic related with artifacts (sampling rate: 120Hz)

4 Detection of HR

The impulsive artifacts of the SpO_2 are usually caused by abrupt motions of subject's fingers and it can be generated by utterances, coughs, etc. gives impulsive artifacts to SpO_2 signals. So, simple peak detection methods based on differentiation cannot be effective to the HR estimation. Generally, pitch detection based on auto-correlation can be thought robust and appropriate to the HR estimation.

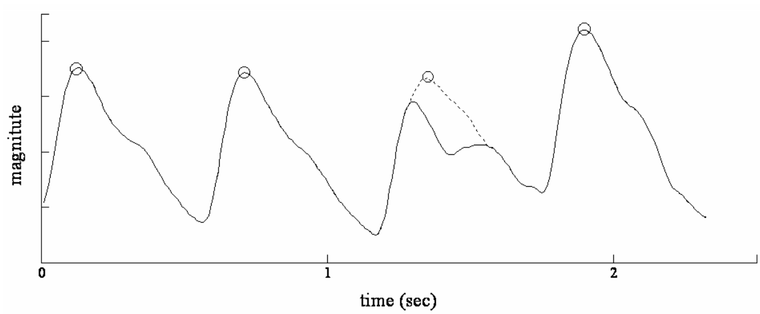


Fig. 2. Example of heart beat point distortion in SpO_2 signal(dotted line: expected SpO_2 curves without artifacts, circle mark: heart beat point)

Even though auto-correlation can find stable pitches, the problem such as halvings or doublings of their true values can occur frequently. Besides, severe noises can be included to the SpO_2 signal. To prevent the problems, median filtering is used to ensure the performance of HR detection.

5 Frequency Domain Analysis to Detect Respirations

A BPF with a fixed passband has no functionality for the overlapped range of an HR and an RR. It can be only applicable to little intensive exercises having no overlapped range. For an exercise with the RR of 0.1~1.4Hz, the filtering cannot detect respiration points in the SpO_2 signal faithfully.

On the other hand, because the proposed algorithm can move the passband dynamically, it can work robustly for exercises of various intensities in detecting respirations. Especially, the SpO_2 signal which contains maximum intensity of exercise is also under coverage.

As a preliminary estimation of the RR, the frequency analysis is performed. The pre-estimation make it possible to adjust the BPF to have a narrow passband near the RR. The properly chosen passband achieves successful results in detecting respirations by blocking heart beats and artifacts.

Fig. 3 shows why a fixed BPF with a wide passband is not appropriate. The result of the bandpass filtering is nothing of heart beats or respirations. But, the result of the bandpass filtering near the RR successfully extracts respiration points from the SpO_2 signal.

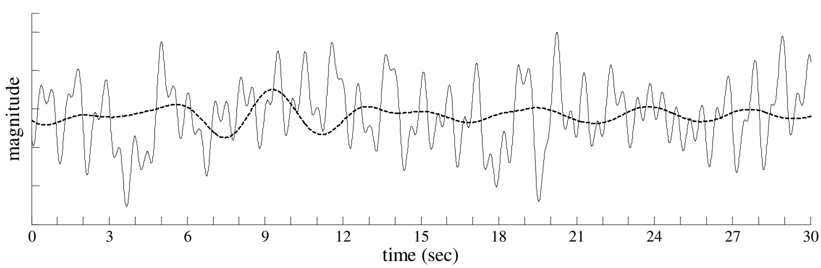


Fig. 3. HR: 2.0Hz and RR: 0.5Hz at 150Watt-loaded exercise (solid line: bandpass filtering(0.1~1.4Hz), dashed line: bandpass filtering(0.4~0.6Hz))

6 Overall Procedure of Proposed RR Detection

Fig. 4 shows the overall block diagram of the proposed algorithm to detect respirations using the input SpO_2 signal. Initially, the HR is obtained by calculating the autocorrelation contour. Because the HR reflects the circulation of blood, it can be used as a factor of the load of an exercise. In calculating the HR from the autocorrelation contour, the time between two adjacent peak points may be half or doubling frequently. So, median filtering as a post-processing is useful to reduce those kinds of errors.

In the frequency domain analysis by the FFT(Fast Fourier Transform), candidate RR elements are selected by the HR. Among the candidates, the most strong frequency element is recognized as the true RR. Subsequently, the estimated RR determines the passband of the BPF. Finally, the detection of respiration points is easily performed by finding local maxima after the bandpass filtering because the BPF blocks various artifacts including heart beats in the SpO_2 signal.

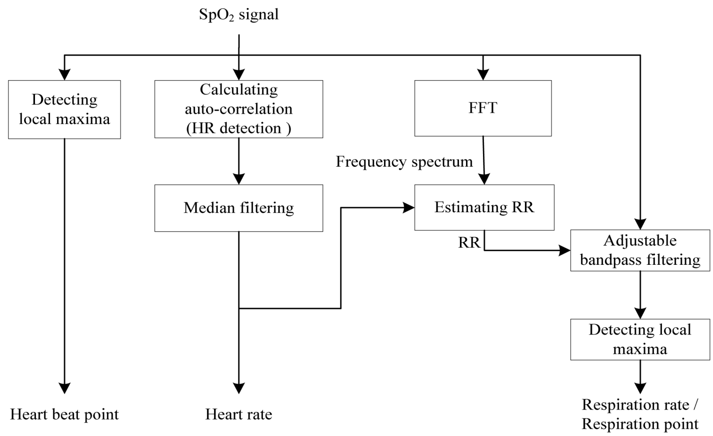


Fig. 4. Block diagram of proposed algorithm

7 Experiments and Results

The first experiment was designed for the evaluation of the proposed algorithm when general intensity was imposed to subjects during exercise. To evaluate the performance of the proposed algorithm, 50~150Watt was loaded to pedals of a bicycle-type exercise machine. Five men in the ages from 20's to 30's were tested. They were exercised for 5 minutes with the loads of 50, 100, and 150Watt on the machine. At the end of each session, a short break of 1~2 minute was served. During exercise, no artificial restriction was given to the subjects, that is, they were able to breathe freely.

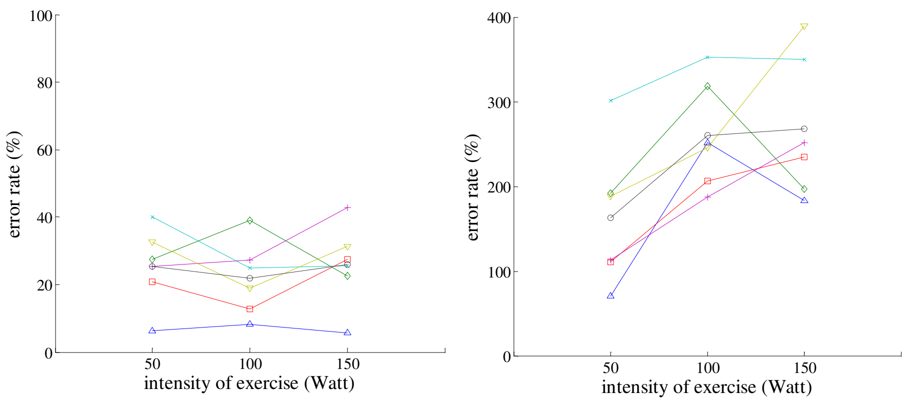
When we record SpO_2 signals, the ECG impedance data was also recorded simultaneously to verify the result of the respiration detection. If the time difference between a detected respiration and its true respiration is larger than a wavelength of the latter, we declared an error. The sampling rate of the recorded date was 120Hz, and it was quantized by 10 bits.

The second experiment was designed to evaluate the performance when maximum intensity of exercises was imposed to the subjects. This experiment was aimed to verify the necessity of the broadband processing of the proposed algorithm. Three men in the ages of 20's were tested. Within the maximum load(150Watt) of the exercise machine, we tried to induce the maximum HR and RR.

Whole results of the experiments are arranged in Fig. 5 and 6. All error rates were calculated by Eq. (1).

$$\text{error rate}(\%) = \frac{z}{x} \times 100 \tag{1}$$

Where, x and z are the true and the detected RR, respectively. The true RR is obtained by the information of ECG impedance. The total average of the proposed algorithm and the conventional fixed BPF method shows respiration detection error of 20.32% and 196.40%, respectively. The conventional method detected false respiration points frequently as shown in its performance.



(a) error rate of proposed algorithm (b) error rate of fixed band pass filtering

Fig. 5. Results of normal exercises(circled line: average of all subjects, the others: each subject)

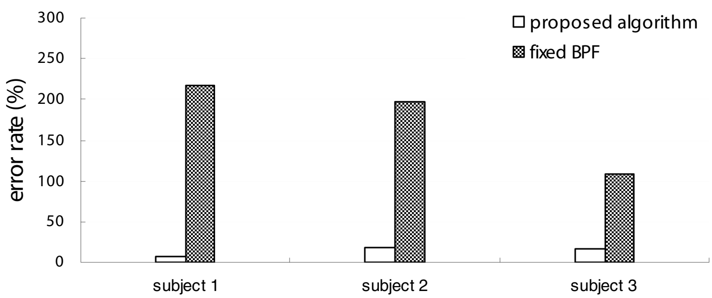


Fig. 6. Results of exercises loading maximum intensity

For the exercises imposing normal loads, the RR estimation errors were 25.40%, 21.84%, and 25.88% for the exercise loads of 50Watt, 100Watt, and 150Watt, respectively. The average error rate of the proposed algorithm was 24.37%. When the conventional fixed passband BPF method was utilized, the RR estimation errors were 162.67%, 260.20%, and 267.66% for each load. The average error rate of the conventional method was 230.17%.

For the exercises imposing maximum loads, the RR estimation errors were 14.10% and 174.43% for the proposed and the conventional method, respectively. The experimental results are summarized in Fig. 6.

8 Discussion

In order to verify the performance improvement by the proposed algorithm, the conventional bandpass filtering with a fixed passband and the adjustable bandpass filtering were evaluated in the respiration range of 0.1~1.4Hz. The proposed algorithm showed significantly better performances than the conventional method for various experiments. Moreover, it is more effective for the RR estimation in intensive exercise conditions than in relatively less intensive ones. This is because the internal respiration in bloods become more intensive as the load of an exercise is increased.

When the intensity of exercise is changed, the 100Watt load exercises show the highest error reduction. It means that, under a proper intensity of exercise, the magnitude of the respiration component in SpO_2 signals can be much stronger than that of artifacts. When the load of an exercise increases a certain threshold, subjects tend to increase the amount of breathing to obtain much oxygen rather than to increase the counts of respirations. It widens the difference between the actual external respiration and the respiration detection result from SpO_2 signals.

9 Conclusion

Through the experiments, it was shown that the proposed algorithm guarantees robust performances for various exercises. Although the performance may not be appropriate for medical monitors in hospitals, it is affordable for home exercise machines sufficiently. Our algorithm can be applicable to various embedded health care systems and contributes to the acceleration of the supply of them to users at their own home.

As a further work, it is important to investigate the relationship between the respiration and the condition of users in exercising. To do this, studies for the evaluation of exercise habits of individuals are essential. In addition to pulse oximetry, breathing or groan sound will be analyzed to evaluate exercise habits of users. This makes possible user-specific guidance to the adequate load of an exercise.

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