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A Novel Respiratory Rate Estimation Method for Sound-Based Wearable Monitoring Systems

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Abstract—**The respiratory rate is a vital sign that can provide important information about the health of a patient, especially that of the respiratory system. The aim of this study is to develop a simple method that can be applied in wearable systems to monitor the respiratory rate automatically and continuously over extended periods of time. In this paper, a novel respiratory rate estimation method is presented to achieve this target. The proposed method has been evaluated in both the open-source data as well as the local-hospital data, and the results are encouraging. The findings of this study revealed strong linear correlation to the reference respiratory rate. The correlation coefficients for the open-source data and the in-hospital data are 0.99 and 0.96 respectively. The standard deviation of the estimation error is less than 7% for both types of data.**

I. Introduction

RESPIRATORY rate is a vital sign that can provide important information on a patient's health. Abnormal respiratory rate could indicate a variety of conditions including respiratory diseases as well as systemic abnormalities including cardiovascular abnormalities and acidosis. The respiratory rate is also a commonly used parameter in routine patient monitoring to detect early disease and deterioration in clinical conditions. For example, respiratory rate is a useful indicator in severe asthma [1]. Despite its importance and widespread utility, there is a lack of simple respiratory rate measurement instruments that can be applied in clinical practice. In most centers today, manual measurement of respiratory rate is still routinely practiced and this is time consuming and labor intensive.

The gold standard for respiratory rate estimation is through the measurement of respiratory flow using a pneumotach or using a capnograph [2]. However, these methods are not only expensive but also inconvenient and are not practical for extended monitoring. Therefore a more practical and simple method is needed for continuous respiratory rate monitoring over extended periods of time.

With the rapid development of electronic sensors and computer technology, computer-aided respiratory monitoring employing electronic sensors has been investigated. Considering system complexity, cost and safety factors, our work focuses on a common method for respiratory rate estimation which is based on sound signals. Some studies on sound-based respiratory rate estimation have been presented in [3-5]. Although the methods in these papers are reported to have good performance, they may be complex to implement and hence not be suitable for wearable devices which have rigid restrictions on computational complexity, memory and power consumption.

In this paper, a novel method for respiratory rate estimation using acoustic signals is described. The technical objective of the study is to develop a simple method that can be used in wearable systems to monitor the respiratory rate automatically and continuously over extended durations. The rest of the paper is organized as follows. Section II introduces the framework of the proposed respiratory rate estimation method which includes the collection and use of the data, the detailed explanation of the proposed original and enhanced methods and the implementation of the method in a wearable system. Section III presents the results and discussions and Section IV covers the conclusion.

II. Materials and Methods

A. Data Collection

Real data of nine volunteers were collected in practical environment (either in the clinic or the ward of a local hospital). Institutional review board (IRB) approval was obtained for data collection from clinical subjects and informed consent was obtained.

All volunteers were young male patients with asthma (7.13±1.81 years, weight 25.73±5.96 kg). Respiratory sounds were recorded over the right side of the chest-wall using an acoustic sensor (ECM microphone with cavity for air-coupling purpose). The sensor did not require direct contact the subjects' skin. The sampling rate was 8k samples/second and recording period was 5 minutes.

B. Data Used for This Study

Two types of data were used for this study. The first type was a set of data samples from open resources [6-8] and was studied for comparison purposes. These open-source data were in good quality (i.e. low noise, neither speeches nor other interferences) and are with length of 10-30 seconds.

The other type was a group of respiratory sound signals obtained from the data collection which was described in Section II.A. As respiratory rate changes over time, in order to update this variation promptly, the sound signal was segmented into 15s frames. The duration of breathing cycle was estimated every 15s and the result was then translated into the respiratory rate in a full minute.

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C. Reference Respiratory Rate

Accurate measurement of respiratory rate is very difficult with existing technologies. Even with gold standard reference methods (e.g. airflow measure) there are still errors involved. A common practice in hospitals is to count the thoracic or abdominal movement manually for 15-30s and then multiply the correspondent times to get the number of breaths in a full minute. Another method to obtain the reference respiratory rate is to examine the waveforms of the data visually using appropriate software. In this study, the mean value of the rates obtained via the above-mentioned methods was used as the reference comparator. For the data frames with severe noises or interferences resulting in unreliable reference respiratory rates, these data samples were excluded from the study.

D. Method for Respiratory Rate Estimation

The block diagram of the proposed method for respiratory rate estimation is depicted in Fig.1. The algorithm consists of four major steps, i.e. Short-Time Fourier Transform (STFT), peak detection by masking, entropy-based feature extraction, autocorrelation-based respiratory rate estimation. The details of these processing steps will be explained in detail below.

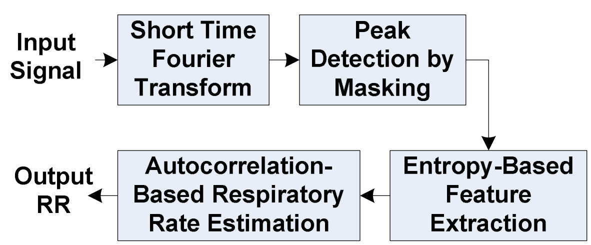

Fig.1. Block diagram of proposed respiratory rate estimation method

1) Algorithm

The signal to be processed can be written as

$$s(t) = r(t) + n(t) \tag{1}$$

where $r(t)$ represents the signal of respiratory sound and $n(t)$ denotes non-respiratory sounds like noise, speech and other interference. $s(t)$ can be transformed to the frequency domain using the STFT [9]

$$S(\tau, f) = \int_{-\infty}^{+\infty} s(t) h^*(t-\tau) e^{-j2\pi f t} \mathrm{d}t \tag{2}$$

where $h(t-\tau)$ is the window function, τ is the shift in time and "*" represents the complex conjugate.

After the frequency components of the respiratory signal have been given out by the STFT, the frequency components with dominant values can be identified by averaging filtering the result of the STFT, where the peak components will mask the adjacent components with lower values. The peak detection is achieved by

$$S_p(n,f) = \begin{cases} S(n,f) - S_a(n,f) & \text{if} \quad S(n,f) > S_a(n,f) \\ 0 & \text{if} \quad S(n,f) \le S_a(n,f) \end{cases} \tag{3}$$

where $S_a(n,f) = {}^1\!/_L \cdot \sum_{n=1}^{L} S(n,f)$ and L is the length of the averaging filter.

Recalling the origin concept of Shannon entropy defined in [9], a similar concept can be applied here to describe the characteristics of power distribution of the respiratory signal. The entropy defined in this study has not the exact description as Shannon entropy but in a similar way. Assuming there are N dominant components of $S_p(n,f)$ whose values are greater than zero, and these peak values are represented by $C_1, C_2, \cdots, C_N$, a weight for each dominant component can be measured by the proportion between the power of the specific dominant component and the total power sum of all these dominant components, i.e.

$$p_n = \frac{C_n}{\sum_{n=1}^{N} C_n}, \qquad n = 1, 2, \cdots, N. \tag{4}$$

The entropy can be calculated using these weights as follows.

$$E_t = -\sum_{n=1}^{N} p_n \log_b(p_n). \tag{5}$$

The entropies of a series of STFT outputs can be averaging filtered along the time axis. The feature chosen in this study is the smoothed entropies which is given by

$$E_a = \frac{1}{M} \sum_{t=1}^{M} E_t \tag{6}$$

where M is the length of the smoothing filter.

Noting the fact that respiratory signal is a periodical signal (although it is not a pure periodical signal as sine wave and its periodicity is slowly changing during time), autocorrelation function can provide the information about the periodicity of the respiratory signal. The extreme values in the extracted features are identified and the autocorrelation function on the positions of these values gives the periodicity of the breathing cycle.

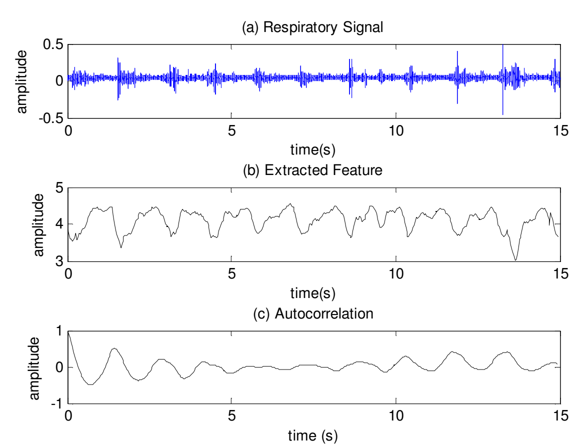

Fig.2. Processing results of proposed respiratory rate estimation method ==>>

Fig.2 demonstrates an example of the processing results of the proposed respiratory rate estimation method. Fig.2 (a) shows the waveform of a respiratory sound signal collected from a patient in local hospital. Fig.2 (b) displays the feature extracted from the respiratory signal. Fig.2 (c) represents the autocorrelation function of the features where the second peak corresponds to the breathing cycle. Since the second peak occurs at 1.44s, it means the respiratory rate is equivalent to around 42 breaths per minute.

2) Enhanced Feature for Irregular Breathing Pattern

Some researchers reported that one of the major causes resulting in incorrect estimation of respiratory rate is the presence of complex or irregular breathing patterns. Here we propose a method to enhance the entropy-based feature so that it can be more robust to strange breathing patterns. Unlike the method proposed in II.D.1, in this enhanced method, the minor components in the STFT output will not be discarded directly but replaced by some appropriate small value (e.g. 0.01). In this way, a time-feature improved entropy can be constructed to emphasize the periodical characteristics of the respiratory signal.

In order to illustrate the effect of the proposed enhanced method, the method has been applied to a data sample which contains abnormal breathing patterns. Fig.3 shows the difference between the original feature (black dashed line) and the enhanced feature (red solid line). It can be observed that a peak around 4s in the time-axis in the enhanced feature clearly indicates the finish of a respiratory phase whereas this is not so clear in the original feature. It can also be found that the enhanced feature gives a better description of the breathing pattern during 7-8.4s where an unstable transit phase in the respiration is suppressed.

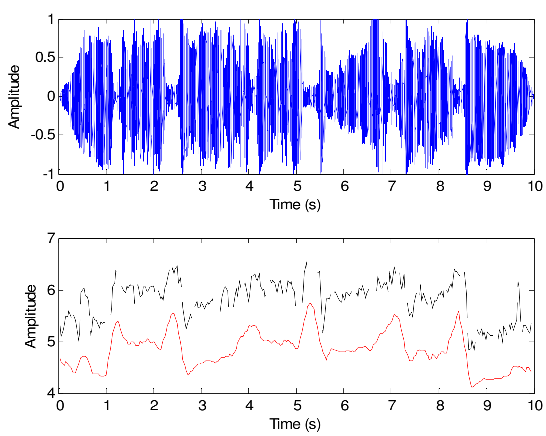

Fig.3. Processing results of enhanced feature for irregular breathing pattern

The principle underlying the proposed enhanced method is explained as follows. Replacing minor components with small-value components in the STFT output is equivalent to introduce wide-band noise in the spectrum. This operation has less effect on the periods where the respiratory signal is strong. However, for those periods where the respiratory signal is weak (i.e. periods between inspiratory phase and expiratory phase), the effect of the introduced wide-band noise would be dominant. Therefore the entropy values during these periods will be increased and the distinguishing between different respiratory phases will be enhanced.

E. Work on Wearable Systems

The development of the respiratory rate estimation method is one part of an existing project to develop wearable systems for monitoring of human's health condition. Two types of wearable systems have been developed, one is PCB-board based system using microchip and the other is based on PDA or smart phone. These wearable systems have been used in various clinical applications such as recording and analysis of respiratory sounds, wheeze detection and heart rate monitoring. Some work of this healthcare project has been presented in our earlier publications [10-13].

The proposed method has been implemented in the PCB-board based wearable system. The block diagram of the processing steps on the wearable system has been depicted in Fig.4. The sound signal captured by the sensor is sent to the board which consists of front-end circuits, a microchip-based processing unit, and a display and storage unit. The weak microphone output is first amplified then filtered by the analog conditioning circuit to enhance the signal of interest frequency range. The enhanced signal is then digitalized by an A/D converter and sent to the microchip-based processing unit where the above-proposed respiratory rate estimation algorithm is applied. The result will be shown on the display unit and the chosen useful information will be stored in the storage unit for future use.

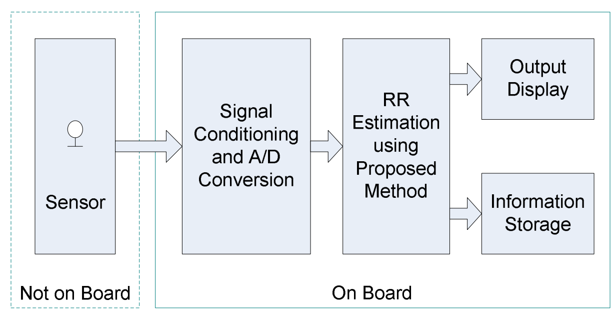

Fig.4. Block diagram of processing steps in wearable system

III. RESULTS AND DISCUSSIONS

In order to validate the proposed respiratory rate estimation method and evaluate its performance, the proposed method was tested using the two types of data described above in section II.B. The test results are presented in Fig.5-6 below. In both figures, the x-axis denotes the reference respiratory rate of a frame and the y-axis denotes the correspondent estimated respiratory rate of the same frame.

Fig.5 shows the results of the proposed respiratory rate estimation method while applied to open-source data. The red stars in the figure present the results of data from patients and the blue circles denote the results of data from healthy subjects. The figure clearly indicates that there is a strong linear correlation between the results of the proposed method and reference respiratory rate. The result of linear curve fitting of the overall data is $y = 1.02x - 0.04$.

The above results also reveal that the proposed respiratory rate estimation method has slightly better performance when tested in healthy subjects than to the data from patients. The correlation coefficients for the former and the latter are 0.9996 and 0.9931 respectively. The standard deviation of the estimation error is 0.64% for the data from healthy subjects and 5.17% for the data from patients. The reason of this difference could be explained as there is higher presence of abnormal breathing patterns in the data from patients.

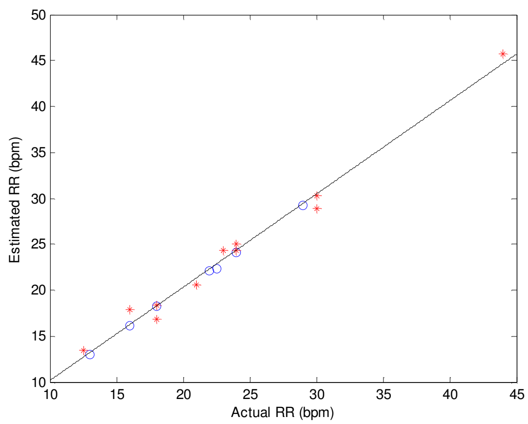

Fig.5. Results of applying proposed respiratory rate estimation method to open-source data (red stars present results of patients and blue circles present results of healthy subjects)

Fig.6 displays the results when the proposed respiratory rate estimation method is applied to the local-hospital data from patients. The results also indicate a strong linear correlation between the results of the proposed method and reference respiratory rate. The correlation coefficient between the estimated respiratory rate and the reference respiratory rate is 0.96. The linear curve fitting of the two methods gives a result of $y = 0.98x + 1.30$. The standard deviation of the estimation error is 6.6%.

It should be noted that the performance of the proposed respiratory rate estimation method has a mild degradation when tested using local-hospital data. This is because there are noises and interferences in real-life application. Further analysis of the data reveals that the main factors affecting the estimation accuracy include speech, cough, medical device noise, rubbing of clothes, low SNR and complex breathing patterns.

IV. CONCLUSION

This paper presents a novel and effective method for estimating the respiratory rate using a sound-based wearable system. The proposed method introduces an enhanced feature that is robust to the complex breathing patterns. Applying this method to both the open-source data and the local-hospital data produces promising results. The correlation coefficients between the estimated respiratory rate and the reference respiratory rate are 0.99 and 0.96 respectively. The overall average error of the proposed method is less than 7%.

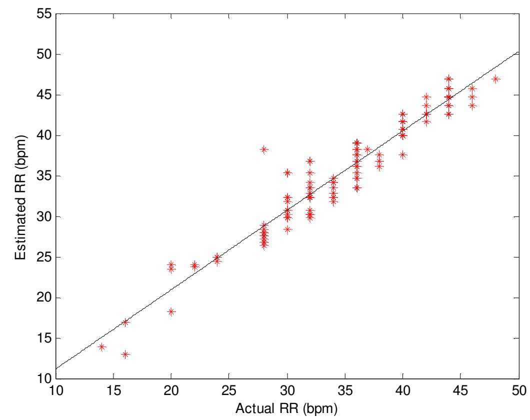

Fig.6. Results of applying proposed respiratory rate estimation method to patients' data from local hospital

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