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Tissue Artifact Removal from Respiratory Signals Based on Empirical Mode Decomposition

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Abstract

On-line measurement of respiration plays an important role in monitoring human physical activities. Such measurement commonly employs sensing belts secured around the rib cage and abdomen of the test object. Affected by the movement of body tissues, respiratory signals typically have a low signal-to-noise ratio. Removing tissue artifacts therefore is critical to ensuring effective respiration analysis. This paper presents a signal decomposition technique for tissue artifact removal from respiratory signals, based on the empirical mode decomposition (EMD). An algorithm based on the mutual information and power criteria was devised to automatically select appropriate intrinsic mode functions (IMFs) for tissue artifact removal and respiratory signal reconstruction. Performance of the EMD-algorithm was evaluated through simulations and real-life experiments (N = 105). Comparison with low-pass filtering that has been conventionally applied confirmed the effectiveness of the technique in tissue artifacts removal.

Keywords

Respiratory Signal Analysis; Empirical Mode Decomposition; Artifact Removal

1. Introduction

Continuous monitoring of respiration in free-living environments is important for quantifying exposure to environmental contaminants in the air. Additionally, respiration measurement provides a physiological response that increases with the intensity of exercise, thus is useful in quantifying an individual's level of physical activity. Compared to the conventional respiratory gas exchange techniques utilizing a mask or mouthpiece, non-invasive techniques are less burdensome to human test subjects, therefore have gained increasing interest from the research community [1-3]. These techniques commonly employ sensing belts, e.g. piezoelectric sensors [4], inductive plethysmography [1], [5], or optical fibers [6], [7], placed around the rib cage and abdomen of the test subject, to measure the chest and abdominal wall expansion. From the frequency and magnitude of dimensional changes of the belts, ventilation can be estimated [8], [9]. However, physical activities in a free-living environment are typically associated with body movement, and the resulting

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tissue artifacts cause significant contamination of the belt signals, and consequently, inaccurate measurement of ventilation [10].

For tissue artifact removal, filtering techniques have been commonly applied [11], [12]. While easy to implement, a priori information of the signal frequency characteristics is needed in order to choose the appropriate cutoff frequency. Also, useful data may be attenuated during the filtering process [13]. Adaptive filtering techniques have been reported for artifact removal [10], [14-16] with additional inputs such as body accelerations as the reference basis [14]. As an example, a finite impulse response (FIR) filter whose coefficients were tuned by modeling the difference between the respiratory signal and accelerometer signal using the least mean square has been shown in [14]. While successful in artifact removal, the need for additional inputs increases the system cost. Recently, wavelet transform has been investigated for respiratory signal denoising [14]. The effectiveness of wavelet transform in feature extraction is dependent on the proper choice of a base wavelet function [17-19].

In recent years, empirical mode decomposition (EMD) [20] has gained increasing attention for biomedical signal processing as this technique is data-driven and self-adaptive. Successful applications of EMD include high frequency interference reduction in surface electroenterogram [21], analysis of human heart-rate signals [22], wall components removal from Doppler ultrasound signals [23], extraction of cortical oscillatory activities from multi-channel magnetoencephalographic (MEG) measurements [24], and coronary and aortic blood flow waveform analysis [25]. EMD has also been applied to respiratory signal analysis for reconstructing respiration from the pressure fluctuation of the contact surface between the test subject and bed under sleeping conditions [26]. Moreover, EMD has been combined with independent component analysis (ICA) for source separation from single-channel electroencephalography (EEG) recording [27].

This paper investigates the utility of EMD for tissue artifact removal from respiratory signals. Details of an EMD-algorithm that automatically selects the intrinsic mode functions (IMFs) based on the mutual information and power distribution are presented in section 2. In section 3, the performance of EMD in removing artifact is first numerically evaluated using synthetic signals constructed from a clean respiratory signal and noise components, and is further evaluated through real-life experiments, where respiratory signals were measured by test subjects performing various types of physical activities – from sedentary (e.g., computer work, filing papers) to vigorous activities (e.g., playing basketball and tennis). Conclusions are drawn in section 4.

2. Methods

2.1. EMD as a Signal Filter

EMD is a data-driven signal processing technique [20] that does not require the data being analyzed to be stationary and linear. EMD decomposes a signal into a sum of IMFs, each of which represents an oscillatory mode. An IMF is defined as a function that has either the same number of extrema and zero-crossing, or the numbers differ at most by one, and the mean value between the upper and lower envelope is equal to zero [20]. As a result of the EMD process, a time-varying signal can be expressed as:

$$x(t) = \sum_{i=1}^n C_i(t) + r_n(t) \quad (1)$$

where n is the number of IMFs, $c_i(t)$ represents the i th IMF, and $r_n(t)$ is the residue of the signal $x(t)$.

The order of the IMFs corresponds to the magnitude of the time scale. The first-extracted IMF has the smallest time scale or the highest dominant frequency present in the original signal. As the decomposition process proceeds, the time scale increases and the dominant frequency decrease. Hence, the signal represented by EMD decomposition in Eq. (1) is the sum of a series of frequency bands, and the EMD algorithm, commonly referred to as a sifting process [20], is essentially an adaptive filtering operation [28] that can be represented by:

$$x_f(t) = \sum_{i=l}^h c_i(t) \quad (2)$$

where $x_f(t)$ is the filtered signal, l and h represent the lower and upper indices of the IMFs, respectively, $l, h \in [1, 2, \dots, n+1]$, and $l \leq h$. For convenience of representation, the residue $r_n(t)$, originally represented in Eq. (1), is given by the $(n+1)^{\text{th}}$ IMF $c_{n+1}(t)$. As a result, Eq. (2) provides a general description of the following filtering operations:

1. high-pass filtering, when $l = 1, h < n+1$;
2. band-pass filtering, when $1 < l \leq h < n+1$;
3. low-pass filtering, when $l > 1, h = n+1$.

By selecting appropriate l and h , features within a certain frequency band can be effectively extracted through the EMD decomposition process.

2.2. Measurement of the Respiratory Signal

Figure 1 illustrates the configuration of a wearable data acquisition system, which includes a belt assembly (Piezo Respiratory Effort, Ambu Inc.) and a respiratory gas exchange system (Oxycon Mobile, CareFusion) used as a reference base.

A piezoelectric sensor is typically used for monitoring test subject respiration. The sensor is combined with an elastic belt to construct a belt sensor where the output signal is proportional to the expansion of the belt. When encircling the abdomen snugly at the level of umbilicus, the belt sensor measures the abdominal expansion associated with the respiratory effort and output signals with a sensitivity of $30 \mu\text{V}/\text{mm}$. The sensor is directly connected to an integrated measurement system (IMS) [29]. Data were sampled at a frequency of 30 Hz by an analog-to-digital converter (ADC) with a resolution of 10 bits/sample, and stored into a secure digital (SD) card. The volume transducer from the respiratory gas exchange system serves as a standard reference. The respiratory gas exchange system is secured to the subject using an adjustable vest. The breath-by-breath respiratory data, e.g., breathing rate and minute ventilation, are collected through a facemask and bi-directional digital volume transducer, and then transmitted wirelessly to a host laptop. The synchronization between the IMS and the host laptop was ensured by dedicated personnel who recorded all the start and stop times of both systems during the data collection process. Calibration of the system is performed before the experiments.

2.3. Composition of Respiratory Signals

The respiratory belt assembly produces a sensor output corresponding to an expansion of the belts. As a result, any muscle movement during physical activities would produce an output, which contaminates the respiratory signal. Such a phenomenon is referred in the presented study as tissue artifact, which consists of small waves riding on top of the main wave of the respiratory signal. These tissue artifacts are random in nature, and their frequency components will vary as the type and intensity of the activity changes over time.

The breathing frequency of a healthy adult at rest is typically 16-18 breaths per minute [30]. The frequency increases as intensity of the physical exercise increases, and may approach 50 breaths/min during high intensity exercise [31]. Tissue artifacts are expressed as rhythmical frequencies that are higher than the frequency of respiration. Generally, output from a respiratory belt can be considered as containing the following components: 1) respiratory component in the lower frequency band, 2) tissue artifact in the higher frequency band, and 3) background noise across all bands.

The frequencies of tissue artifact vary with the type and intensity of movement, and therefore it is difficult to choose one specific cutoff frequency that suits all conditions without losing useful information. In addition, pre-processing procedures are needed to obtain a priori information of the frequency characteristics of a respiratory signal in order to choose a proper cutoff frequency. In contrast, the EMD method has potential to effectively remove tissue artifact due to its adaptive filtering features. Details of the EMD-based tissue artifact removal method are described in the following section.

2.4. Tissue Artifact Removal

A respiratory signal $x(t)$ measured by the piezoelectric sensor may be expressed as:

$$x(t) = x_R(t) + x_N(t) \quad (3)$$

where $x_R(t)$ is the respiratory component, and $x_N(t) = x_A(t) + x_E(t)$ represents the noise component, including tissue artifact $x_A(t)$ and background noise $x_E(t)$. Analysis has shown that the tissue artifacts and background noise are usually present in a higher frequency band than that of the respiration signal. Therefore, these artifacts and noise can be removed by reconstructing the respiratory component using part of the IMFs in the lower frequency band. A critical step to achieve this goal is to determine the index of the IMF from which the partial reconstruction is performed. Such an index is defined as the reconstruction index (RI), which separates all the IMFs into two frequency bands: the one before the RI are in high frequency band, corresponding to tissue artifact and background noise; while IMFs starting from the RI to the residue are in the lower frequency band, corresponding to the respiratory component. The determination of the RI will be explained in the later section.

By replacing the IMFs in the high frequency band with zeros, the tissue artifact and background noise are removed and the respiratory signal is reconstructed by summing up the remaining IMFs and residue. Thus, decomposing the respiratory signal $x(t)$ using EMD leads to:

$$x(t) = \sum_{i=1}^{n+1} c_i(t) \quad (4)$$

where $c_i(t)$ represents the i th IMF, and $c_{n+1}(t)$ represents the residue $r_n(t)$ as defined in Eq. (1). Assuming the RI is K , the noise component can be estimated as:

$$\tilde{x}_N^{(K)}(t) = \sum_{i=1}^{K-1} c_i(t) \quad (5)$$

where $K = 2, \dots, n+1$. The respiratory component at the reconstruction index of K is estimated as

$$\tilde{x}_R^{(K)}(t) = \sum_{i=K}^{n+1} c_i(t) \quad (6)$$

Similarly, if the RI is $K+1$, the estimated respiratory and noise components are expressed as $\tilde{x}_N^{(K+1)}(t)$ and $\tilde{x}_K^{(K+1)}(t)$, respectively. It is seen from the above derivation that to extract the respiratory component, the key is to determine the RI, and the following two properties of the signal serve as criteria for the identification of the RI.

1) Mutual information—The mutual information quantifies the amount of dependence or shared information between two variables, and is used as the first criterion to identify the RI. The mutual information between the respiratory and noise components is expressed as

$$I(x_R(t), x_N(t)) = \sum_{x_R(t)} \sum_{x_N(t)} p(x_R(t), x_N(t)) \log \left(\frac{p(x_R(t), x_N(t))}{p(x_R(t)) p(x_N(t))} \right) \quad (7)$$

where $p(x_R(t))$ and $p(x_N(t))$ are the marginal probability distribution functions of the respiratory and noise components, respectively, $p(x_R(t), x_N(t))$ is the joint probability distribution function of the two components, and the log is to the base of 2. Since the respiratory and noise components are discrete variables (sampled by an Analog-Digital Converter), double summations are performed in Eq. (7). For continuous variables the operation will be replaced by double integrals. Ideally, the respiratory and noise components are independent from each other, and therefore $p(x_R(t), x_N(t)) = p(x_R(t)) p(x_N(t))$. As a result, the mutual information between the two components becomes zero.

Assume that $MI(K)$ represents the mutual information of the estimated respiratory and noise components, expressed as

$$MI(K) = I(\tilde{x}_R^{(K)}(t), \tilde{x}_N^{(K)}(t)), \quad K \in \{2, \dots, n+1\}, \quad (8)$$

Specially for $K=1$, it can be considered that there is no noise component in the respiratory signal, and therefore $MI(1) = 0$. An example of the $MI(K)$ values for different indices is illustrated in Fig. 2. It is seen that the $MI(K)$ values have shown a distinct trend that the values are relative small and close to zero for the first several indexes until $K=5$. Starting at the index of 6, an abrupt increase of the $MI(K)$ value is shown and after that, the $MI(K)$ values are higher than those at K less than 6. It is assumed that the first few IMFs correspond to the tissue artifact and background noise components, which ideally are independent from each other. As a result, the first few $MI(K)$ values before the index of 6 are close to zero. On the other hand, for any index that is greater than 5, the corresponding estimated noise component will incorporate part of the respiratory component. Therefore, the estimated respiratory and noise components would contain certain amount of shared information, leading to the increasing of the $MI(K)$ values. This abrupt increase of the $MI(K)$ value identifies the optimal RI (5 in this example), which can be determined by the ratio of the mutual information (MIR) of two adjacent indices, defined as

$$MIR(K) = \frac{MI(K+1)}{MI(K)}, \quad K=2, \dots, n. \quad (9)$$

The index that has the largest MIR value is therefore determined as the optimal RI.

Such a mutual information based criterion would require $n-1$ steps of calculating the $MI(K)$, which could be computationally inefficient for real-time applications. By combining the

following power based criterion, it is expected that the computational cost would be reduced by half. 2) *IMF power distribution*. The power content is a direct measure of a signal's strength, and can be used to characterize the IMF. Given that the respiratory component is dominant in the respiratory signal, the power of the respiratory component is greater than that of the noise component. Specifically, the power of each IMF can be used as the first criterion for determining the reconstruction index. By assuming the signal is applied to a 1-ohm load, the power of the i th IMF $c_i(t)$ is defined as

$$P_{c_i(t)} = \frac{1}{M} \sum_{j=1}^M c_i^2(j) \quad (10)$$

where M is the total number of sampled data. For example, the value of M is 1,800 for a signal of 60 seconds when sampled at 30 Hz. The IMF that has the largest power is considered as a dominant part in $x_R(t)$, and its index K' is determined as an initial reconstruction index:

$$K' = \arg \max_i P_{c_i(t)} = \{i | \forall j: P_{c_j(t)} \leq P_{c_i(t)}\} \quad (11)$$

where $\arg \max$ is the argument of the maximum, which finds the index i of which the IMF contains the largest power. Such a power-based criterion identifies a “coarse” reconstruction index, that the IMFs starting from the index K' to the residue are parts of $x_R(t)$. Thus, it is only needed to calculate the mutual information from $MI(2)$ to $MI(K')$, which would reduce the computational cost significantly.

Therefore, the following steps summarize the EMD-based tissue artifact removal algorithm:

Algorithm

EMD-based Tissue Artifact Removal

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- 1 Perform EMD on a measured respiratory signal and obtain all the decomposed IMFs as shown in Eq. (4).
 - 2 Calculate the power of each IMF by Eq. (10).
 - 3 Identify the “coarse” reconstruction index K' by Eq. (11).
 - 4 Calculate the mutual information $MI(2)$, $MI(3)$, ..., $MI(K'-1)$, $MI(K')$ using Eq. (8).
 - 5 Calculate the mutual information ratio $MIR(2)$, $MIR(3)$, ..., $MIR(K'-1)$ by Eq. (9).
 - 6 The final reconstruction index K is identified as the one that corresponds to the largest MIR value.
 - 7 Reconstruct the respiratory component by Eq. (6).
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3. Results

3.1. Simulation Evaluation

The effectiveness of the EMD method in tissue artifact removal was first evaluated through simulation with synthetic respiratory signals expressed as

$$s(t) = x_R(t) + x_N(t) \quad (12)$$

where $s(t)$ represents a synthetic signal, consisting of a “clean” respiratory component $x_R(t)$ which is considered as free of noise, and a noise component $x_N(t)$ which is either a synthetic noise or a real noise reconstructed from measured signal.

Fig. 3 shows the respiratory component and several examples of synthetic tissue artifacts. Specifically, the respiratory component was chosen from a measured respiratory signal during rest with a dominant frequency of approximately 0.25 Hz and the noise component was selected from four different cases: background noise only, tissue artifact only, background noise plus tissue artifact, and real noise from measured signals.

The level of the noise component is determined by the signal-to-noise ratio (SNR) defined as

$$SNR = 10 \log_{10} \frac{\sum_{j=1}^M x_R^2(j)}{\sum_{j=1}^M x_N^2(j)} \quad (13)$$

where M is the total number of the data, $x_R(j)$ and $x_N(j)$ are discrete versions of $x_R(t)$ and $x_N(t)$, and zero means are assumed.

The performance was assessed quantitatively by the signal-to-error ratio (SER), expressed as

$$SER = 10 \log_{10} \frac{\sum_{j=1}^M x_R^2(j)}{\sum_{j=1}^M [x_R(j) - \tilde{x}_R(j)]^2} \quad (14)$$

where M is the total data points, and $\tilde{x}_R(j)$ is the estimated respiratory component. In this study, the traditional Butterworth low-pass filtering of order 8 denoted as LPF is used as the comparison technique [32]. The cutoff frequency is set at 0.5 Hz [14], corresponding to the dominant frequency of the respiratory component at about 0.25 Hz. By definition, a high SER value indicates good performance in artifact removal.

3.1.1 Case 1: Background Noise Only—In this case, the background noise was simulated as Gaussian white noise $x_{GN}(t)$, and the synthetic signal was formulated as

$$s(t) = x_R(t) + A_{GN} x_{GN}(t) \quad (15)$$

where A_{GN} is the amplitude of $x_{GN}(t)$. Five synthetic signals were constructed with SNR selected from 2 dB, 6 dB, 10 dB, 14 dB, and 18 dB, respectively. The amplitude A_{GN} in each synthetic signal was calculated by Eq. (13).

Figure 4 shows the mutual information and power distribution of the IMFs after applying the EMD-based technique to the synthetic signal with the SNR of 2 dB. It is seen that the reconstruction index K was chosen as 6 based on the tissue artifact removal algorithm, and the EMD-based technique has yielded an SER of 14.54 dB, 20% more than that by LPF.

The SER results from EMD and LPF are shown in Fig. 5. It is seen that the EMD-based technique performs better than LPF in removing background noise under different SNRs. Specifically, the performance of the EMD-based technique has outperformed LPF drastically with the SNR increasing, e.g., from 20.4% at SNR = 2 dB to 107.9% at SNR = 19 dB.

3.1.2 Case 2: Synthetic Tissue Artifact Only—As discussed in previous section 2.3, a tissue artifact during movement can be considered as a rhythmical signal with a relative high

frequency. For the purpose of simple evaluation, the tissue artifact was represented by a sinusoidal signal, and the synthetic signal was then expressed as

$$s(t) = x_R(t) + A_{TA} \sin(2\pi f_{TA}t + \theta_{TA}) \quad (16)$$

where A_{TA} , f_{TA} , and θ_{TA} are the amplitude, frequency, and initial phase of the tissue artifact, respectively. The amplitude A_{TA} was determined by Eq. (13) for a set of predefined SNRs (4 dB, 10 dB, 16 dB, 22 dB). The frequencies were chosen as 0.40 Hz, 0.55 Hz, 0.70 Hz, and 0.85 Hz, mimicking the tissue artifacts under activities of various intensities. The initial phase was chosen as 30 degrees. Fig. 3 (b), (c) and (d) show three examples of such synthetic tissue artifacts. A total of 16 synthetic signals were therefore constructed. Three synthetic signal examples in both time and frequency domains are shown in Fig. 6 (a), (b) and (c).

The SER results from EMD and LPF are listed in Table 1. The EMD-based technique outperforms the LPF most of the time except when the SNR was less than 10 dB and the frequency resolution between the respiratory component and tissue artifact was less than 0.3 Hz. This study has demonstrated that the proposed EMD-based technique will outperform the traditional LPF method by at least 19%, under the following scenarios 1) when the frequency resolution is greater than 0.3 Hz and SNR is greater than 10 dB, or 2) when the SNR is greater than 4 dB and the frequency resolution is greater than 0.45 Hz. It is also seen that the EMD-based technique has shown better SER results when the SNR improves or the frequency resolution increases, which demonstrate the self-adaptiveness advantage of the EMD-based technique.

3.1.3 Case 3: Background Noise with Synthetic Tissue Artifact—In this case, the synthetic signal was formulated as a combination of the respiratory component, background noise simulated by Gaussian white noise and tissue artifact simulated by a sinusoidal signal. The synthetic signal is expressed as

$$s(t) = x_R(t) + A_{GN}x_{GN}(t) + A_{TA} \sin(2\pi f_{TA}t + \theta_A) \quad (17)$$

The amplitudes A_{GN} and A_{TA} were designed to have the same SNR for the background noise and tissue artifact, shown as

$$SNR = \frac{\sum_{j=1}^M x_R^2(j)}{\sum_{j=1}^M A_{GN}^2 x_{GN}^2(j)} = \frac{\sum_{j=1}^M x_R^2(j)}{\sum_{j=1}^M A_{TA}^2 \sin^2(2\pi f_{TA}j + \theta_{TA})} \quad (18)$$

An example of such a synthetic signal with $f_{TA} = 1$ Hz, $\theta_{TA} = 30^\circ$, and $SNR = 14$ dB is shown in Fig. 6 (d), with its tissue artifact shown in Fig. 3 (e). Fig. 7 shows the mutual information and power of each IMF for the synthetic signal, and it is seen that the reconstruction index K was determined as 5 according to the criterion. As a result of the EMD-based technique, the SER value after tissue artifact removal is 17.67 dB, which is 32.3% more than that of LPF (13.36 dB). Such result has demonstrated that the EMD-based method is more effective than LPF in this case.

3.1.4 Case 4: Real and Experimental Tissue Artifact—The respiratory component was combined with real tissue artifacts which were extracted from measured respiratory signals during three activities of various intensities, e.g., slow walking, fast walking and running. The Gaussian white noise was also integrated as the background noise. Thus, the synthetic signal was formulated as

$$s(t) = x_R(t) + A_{GN} x_{GN}(t) + A_{RTA} x_{RTA}(t) \quad (19)$$

where A_{RTA} represents the amplitude of the real tissue artifact in this synthetic signal. Similar to Case 3, the amplitudes A_{GN} and A_{RTA} were designed to have the same SNR for the background noise and real tissue artifact. In this case, the SNR was chosen as 12 dB. The real tissue artifacts were constructed by Inverse Fourier transform, expressed as

$$x_{RTA}(t) = \sum_{j=1}^{N_{TA}} A_j \sin(2\pi f_j t + \theta_j) \quad (20)$$

where N_{TA} is the number of sinusoidal elements whose frequencies were larger than 0.5 Hz which were determined as the real tissue artifact components, A_j , f_j , and θ_j represent the amplitude, frequency and initial phase, respectively, and the values of these parameters were determined by the Inverse Fourier transform function. An example of such parameters of the frequency components of the real tissue artifact during running is shown in Table 2, and the corresponding tissue artifact waveforms and frequency spectra are shown in Fig. 3 (f), (g), and (h), respectively. The three synthetic signals with their respective spectra are shown in Fig. 6 (e), (f), and (g).

The synthetic signal during fast walking, illustrated as a portion of Fig. 5 (f), is shown in Fig. 8. The tissue artifact is removed by the two signal processing techniques described. The result is compared with the “clean” respiratory component $x_R(t)$ of the synthetic signal $s(t)$. As seen in Fig. 8 (c), the EMD-processed signal has smaller error than that of the LPF-processed signal, shown in Fig. 8 (b), thus EMD has consistently outperformed LPF. Specifically, the EMD-based technique performs better during higher intensity activities. For example EMD-based technique is about 16% more effective than LPF during slow walking, but about 40% better when data from running are processed. This finding is similar to the results found in Case 2, and further demonstrates the self-adaptiveness of the EMD-based technique. In Table 3, the SER results from EMD and LPF are comparatively listed.

3.1.5 Comparison with Wavelet Analysis—A comparative study has been conducted to evaluate the performance in artifact removal by the proposed EMD algorithm and wavelet analysis, as reported in a previous study [14]. Discrete wavelet transform (DWT) with 4 levels of decomposition [14] was investigated to remove tissue artifact from the synthetic signal, as described in Case 3. Specifically, five different base wavelets, Haar, Daubechies with orders of 2 (Daub2), 4 (Daub4), 10 (Daub10), and 20 (Daub20), were investigated for signal decomposition. In the study, soft thresholding was applied to the DWT coefficients for removing those coefficients that were related to tissue artifacts [14]. The removed coefficients were then replaced with zeros. Subsequently, an inverse discrete wavelet transform (iDWT) was performed to reconstruct the signal. The reconstructed signal is considered as the respiratory component. SER values between the reconstructed and original respiratory signals were then calculated according to the assessment criteria, and compared with those obtained by the EMD-based technique.

Table 4 shows the comparison results of the SER values from EMD, LPF and DWT methods, respectively. It is seen that the EMD-based technique yields the best SER result. For different base wavelets, the DWT method has different SER values. Specifically, the Daub2 has output the best result among the five base wavelets, while the Haar wavelet was not successful, generating SER values that are smaller than that obtained by LPF. The results demonstrate that the performance of wavelet-based denoising techniques is affected

by the choice of proper base wavelet. In comparison, the proposed EMD-based technique is signal agnostic and effective in removing tissue artifact adaptively.

3.2. Real-Life Experimental Evaluation

The performance of the EMD-based tissue artifact removal technique has also been evaluated during real-life experiments, where a total of 105 healthy subjects (44 male, 61 female) were recruited. The group has the following characteristics (mean $\pm$ standard deviation): age = 34.7 ± 14.2 years, weight = 68.7 ± 17.1 kg, height = 166.8 ± 11.3 cm, and body mass index = 24.4 ± 4.5 kg/m². Each participant read and signed an informed consent document approved by the institutional human subjects' review board (at the University of Massachusetts Amherst). Each subject completed activities in one of the two following activity routines 1) computer work (CW), moving boxes (MB), cycling with 1-kp resistance (C1), level treadmill walking at 3.0 mph (T3-0), treadmill walking at 3.0 mph 5% grade (T3-5), treadmill walking at 4.0 mph with 5% grade (T4-5), and tennis (TE); and 2) filing papers (FP), vacuuming (VA), self-paced walk (SW), cycling with 2-kp resistance (C2), treadmill walking at 4.0 mph with 0% grade (T4-0), treadmill jogging at 6.0 mph and 0% grade (T6-0), and basketball (BA). Subjects were allowed to skip the high-intensity activities if they chose to (e.g., treadmill at 6.0 mph, basketball or tennis). Each activity, when performed, lasted for 7 minutes and was followed by a 4-minute rest period.

The piezoelectric belt sensor and the respiratory gas exchange system in Fig. 1 were worn by subjects during testing. The respiratory signals measured by the piezoelectric belt sensor were used for estimating minute ventilation based on the method described in [9] after tissue artifact removal, and the estimation results were evaluated against the minute ventilation measured by the respiratory gas exchange system. Since it is not feasible to identify the real respiratory component or the tissue artifact present in the signal measured by the piezoelectric belt sensor, the performance of the EMD-based technique on tissue artifact removal was therefore evaluated indirectly against the LPF by comparing the minute ventilation estimation error, including bias and standard deviation (SD), standard error (SE) of the bias, mean percentage error (MPE), and root mean squared error (RMSE).

Time- and frequency-domain features including the 10th and 90th percentiles, and the dominant frequency component, were extracted from the "clean" respiratory signals for each 60-second time segment. These features were then used to train a multiple linear regression model [9] for the minute ventilation estimation. Specifically, the model was trained under a subject-independent approach, where the training took place by using signal features from all but one subject. Such an approach, called leave-one-subject-out cross validation, prevents the model from overfitting. This procedure was repeated for each subject, and the average of each estimation error over all the subjects was reported. These assessment criteria were computed for the LPF- and EMD-based techniques, respectively, and the comparison results are shown in Table 5. It is seen from these results that the EMD-based technique estimates minute ventilation more accurately than the LPF, demonstrating improved tissue artifact removal than the traditional filtering technique.

4. Discussion and Conclusion

In this study, an EMD-based technique for tissue artifact removal from respiratory signals was developed and evaluated through simulations and real-life experimentation. Specifically, a power-based criterion for the IMF selection has been devised, and results have demonstrated their effectiveness in identifying the index of IMF for the subsequent tissue artifact removal and the reconstruction of the respiratory signal.

Previous investigations have shown success in respiratory signal enhancement. For example, applying wavelet analysis and adaptive filtering to signals measured by respiratory inductive plethysmography, Keenan and Wilhelm [14] have demonstrated success in removing artifact without attenuating respiratory information. Bu *et al.* [26] has enabled monitoring of respiration and heartbeat through signals measured by a piezoelectric film sensor during sleep by applying EMD for the source separation. By applying EMD to the respiratory mechanomyographic (MMG) signals, Torres *et al.* [33] showed successful results for the cancellation of low frequency component and achieved higher correlation between respiratory and MMG parameters than those obtained by wavelet-based decomposition method.

Compared to the techniques reported in previous studies, the presented EMD-based technique is appealing due to the advantages that: 1) it does not require a priori knowledge for choosing the cutoff frequency as is the case in low-pass filtering; 2) it requires neither the use of an additional sensor as a reference, which increases the system cost and subject burden as is the case in adaptive filtering, nor the selection of a proper base wavelet for achieving better results as is the case in wavelet-based filtering; and 3) the devised mutual information and power based criteria provides an adaptive approach for the IMF selection and does not rely on a priori knowledge of the frequency bandwidth of the signal and noise components.

While the presented method has shown successful tissue artifact removal, it is computationally more demanding in the signal decomposition process than the traditional LPF method, primarily due to the iterative sifting process of extracting IMFs. For example, the computational time needed for performing one EMD decomposition (about 0.576 second on a 2.4 GHz dual-core Intel i5 processor) is about two orders of magnitude higher than that of LFP (about 0.001 second on the same processor). This may limit its application where tissue artifacts need to be removed in real-time. It is also noted in the simulation studies that synthetic tissue artifacts were mostly periodical, which resemble the actual tissue artifact due to muscle movements during rhythmical activities. When intermittent impulsive noise is present, the presented EMD-based technique, especially the power and mutual information criteria of IMF selection, may not be immediately suitable. Therefore, further research is required, e.g., but considering adding a running window across each IMF to determine valid time segments within the IMF. Also, the median value of the power can be considered as the selection criterion for preventing the scenario from happening, when large power value of a specific IMF occurs, due to impulsive noise spreading in that IMF. Such studies will be performed in future studies.

Simulation results have also identified the lower bound when the presented EMD-based technique outperforms LPF, specifically when the frequency resolution is greater than 0.3 Hz and SNR is greater than 10 dB, or when the SNR is greater than 4 dB and the frequency resolution is greater than 0.45 Hz. One limitation of the presented mutual information based IMF selection method is that it does not address the phenomenon of mode mixing in the decomposed IMFs, especially when the SNR is small and the noise frequency is close to the respiratory signal. This may possibly explain why the LPF has shown to yield better result than EMD-based technique when the noise components are outside (lower than) the above bound. It is noted that such limitation may be overcome by leveraging the fractal dimension analysis as studied in [34], or using Ensemble EMD [35].

Future studies will systematically investigate the performance and limitations of the EMD algorithm as indicated above, for a variety of activities in a free-living setting.

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References

- [1]. Cohen K, Ladd W, Beams D, Sheers W, Radwin R, Tompkins W, Webster J. Comparison of impedance and inductance ventilation sensors on adults during breathing, motion, and simulated airway obstruction. *IEEE Transactions on Biomedical Engineering*. 1997; 44:555–566. [PubMed: 9210815]
- [2]. Varady P, Micsik T, Benedek S, Benyo Z. A novel method for the detection of apnea and hypopnea events in respiration signals. *IEEE Transactions on Biomedical Engineering*. 2002; 49:936–942. [PubMed: 12214883]
- [3]. Binks A, Banzett R, Duvivier C. An inexpensive, MRI compatible device to measure tidal volume from chest-wall circumference. *Physiological Measurement*. 2007; 28:149–159. [PubMed: 17237587]
- [4]. Pennock B. Rib cage and abdominal piezoelectric film belts to measure ventilatory airflow. *Journal of Clinical Monitoring and Computing*. 1990; 6:276–283.
- [5]. Witt J, Fisher J, Guenette J, Cheong K, Wilson B, Sheel A. Measurement of exercise ventilation by a portable respiratory inductive plethysmograph. *Respiratory Physiology and Neurobiology*. 2006; 154:389–395. [PubMed: 16503424]
- [6]. Augousti A, Malettras F, Mason J. Improved fibre optic respiratory monitoring using a figure-of-eight coil. *Physiological Measurement*. 2005; 26:585–590. [PubMed: 16088053]
- [7]. Davis C, Mazzolini A, Murphy D. A new fibre optic sensor for respiratory monitoring. *Australasian Physical and Engineering Sciences in Medicine*. 1997; 20:214–219.
- [8]. Banzett R, Mahan S, Carner D, Brughera A, Loring S. A simple and reliable method to calibrate respiratory magnetometers and RespiTrace. *Journal of Applied Physiology*. 1995; 79:2169–2176. [PubMed: 8847288]
- [9]. Liu S, Gao R, He Q, Staudenmayer J, Freedson P. Improved regression models for ventilation estimation based on chest and abdomen movements. *Physiological Measurement*. 2012; 33:79–93. [PubMed: 22173273]
- [10]. East K, East T, Mathews V. Computerized artifact detection for ventilatory inductance plethysmographic apnea monitors. *Journal of Clinical Monitoring and Computing*. 1989; 5:170–176.
- [11]. Burbank D, Webster J. Reducing skin potential motion artefact by skin abrasion. *Medical and Biological Engineering and Computing*. 1978; 16:31–38. [PubMed: 305999]
- [12]. van Alse J, van Eck W, Herrman O. ECG baseline wander reduction using linear phase filters. *Computers and Biomedical Research*. 1986; 19:417–427. [PubMed: 3769470]
- [13]. Sörnmo, L.; Laguna, P. *Bioelectrical Signal Processing in Cardiac and Neurological Applications*. Elsevier Academic Press; 2005.
- [14]. Keenan D, Wilhelm F. Adaptive and wavelet filtering methods for improving accuracy of respiratory measurement. *Biomedical Sciences Instrumentation*. 2005; 41:37–42. [PubMed: 15850079]
- [15]. Thakor N, Zhu Y. Applications of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. *IEEE Transactions on Biomedical Engineering*. 1991; 38:785–794. [PubMed: 1937512]
- [16]. Augousti A, Malettras F, Mason J. Evaluation of cardiac monitoring using fiber optic plethysmography. *Annals of Biomedical Engineering*. 2006; 34:416–425. [PubMed: 16482413]
- [17]. Bhatia, P.; Boudy, J.; Andreão, R. Wavelet transformation and pre-selection of mother wavelet for ECG signal processing; *Proc. 24th IASTED International Multi-Conference: Biomedical Engineering*; Innsbruck, Austria. 2006; p. 390-395.
- [18]. Wang S, Liu X, Yianni J, Aziz T, Stein J. Extracting burst and tonic components from surface electromyograms in dystonia using adaptive wavelet shrinkage. *Journal of Neuroscience Methods*. 2004; 139:174–184.

- [19]. Bradley A, Wilson W. On wavelet analysis of auditory evoked potentials. *Clinical Neurophysiology*. 2004; 115:1114–1128. [PubMed: 15066537]
- [20]. Huang NE, Shen Z, Long S. The empirical mode decomposition and Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society A*. 1998; 454:903–995.
- [21]. Ye-Lin Y, Garcia-Casado J, Prats-Boluda G, Martinez-de-Juan J. Combined method for reduction of high frequency interferences in surface electroenterogram (EEnG). *Annals of Biomedical Engineering*. 2010; 38:2358–2370. [PubMed: 20232149]
- [22]. Yeh J, Sun W, Shieh J, Huang NE. Intrinsic mode analysis of human heartbeat time series. *Annals of Biomedical Engineering*. 2010; 38:1337–1344. [PubMed: 20119846]
- [23]. Zhang Y, Gao Y, Wang L, Chen J, Shi X. The removal of wall components in Doppler ultrasound signals by using the empirical mode decomposition algorithm. *IEEE Transactions on Biomedical Engineering*. 2007; 54:1631–1642. [PubMed: 17867355]
- [24]. Lee P, Shang L, Wu Y, Shu C, Hsieh J, Lin Y, Wu C, Liu Y, Yang C, Sun C, Shyu K. Single-trial analysis of cortical oscillatory activities during voluntary movements using empirical mode decomposition (EMD)-based spatiotemporal approach. *Annals of Biomedical Engineering*. 2009; 37:1683–1700. [PubMed: 19521773]
- [25]. Dang C, Nenadic Z, Kassab GS. A comparative analysis of coronary and aortic flow waveforms. *Annals of Biomedical Engineering*. 2008; 36:933–946. [PubMed: 18398682]
- [26]. Bu, N.; Ueno, N.; Fukuda, O. Monitoring of respiration and heartbeat during sleep using a flexible piezoelectric film sensor and empirical mode decomposition; *Proc. 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*; Lyon, France. 2007; Aug 22-26. p. 1362-1366.
- [27]. Mijović B, De os M, Gligorić I, Taelman J, Van Huffel S. Source separation from single-channel recordings by combining empirical mode decomposition and independent component analysis. *IEEE Transactions on Biomedical Engineering*. 2010; 57:2188–2196. [PubMed: 20542760]
- [28]. Boudraa A, Cexus J. EMD-based signal filtering. *IEEE Transactions on Instrumentation and Measurement*. 2007; 56:2196–2202.
- [29]. Liu, S.; Gao, R.; Freedson, P. Design of a wearable multi-sensor system for physical activity assessment; *Proc. IEEE/ASME Int. Conf. on Advanced Intelligent Mechatronics*; Montreal, Canada. Jul. 2010 p. 254-259.
- [30]. Beckett, B. *Illustrated Human and Social Biology*. Oxford University Press; Oxford: 1995. p. 78
- [31]. McArdle, W.; Katch, F.; Katch, V. *Exercise Physiology: Energy, Nutrition, and Human Physiology*. Lippincott Williams and Wilkins; 2006. p. 270
- [32]. Liu, S.; He, Q.; Gao, R.; Freedson, P. Empirical mode decomposition applied to tissue artifact removal from respiratory signal; *Proc. 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*; Vancouver, British Columbia, Canada. Aug 20-24. 2008 p. 3624-3627.
- [33]. Torres, A.; Fiz, J.; Jane, R.; Galdiz, J.; Gea, J.; Morera, J. Application of the empirical mode decomposition method to the analysis of respiratory mechanomyographic signals; *Proc. 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*; Lyon, France. Aug 22-26. 2007 p. 1566-1569.
- [34]. Hadjileontiadis L. Empirical mode decomposition and fractal dimension filter: A novel technique for denoising explosive lung sounds. *IEEE Engineering in Medicine and Biology Magazine*. 2007:30–39. [PubMed: 17278770]
- [35]. Wu Z, Huang NE. Ensemble empirical mode decomposition: A noise-assisted data analysis method. *Advances in Adaptive Data Analysis*. 2009; 1:1–41.

Figure 1.
Schematic of the data acquisition system.

Figure 2.
An example of the mutual information criterion.

Figure 3.

Respiratory component and synthetic tissue artifacts. (a) The “clean” respiratory component; (b) Synthetic tissue artifact of $SNR = 4$ dB, $f_{TA} = 0.40$ Hz; (c) Synthetic tissue artifact of $SNR = 10$ dB, $f_{TA} = 0.55$ Hz; (d) Synthetic tissue artifact of $SNR = 16$ dB, $f_{TA} = 0.70$ Hz; (e) Synthetic tissue artifact of $SNR = 14$ dB, $f_{TA} = 1$ Hz, $\theta_{TA} = 30^\circ$; (f) Synthetic tissue artifact of slow walking; (g) Synthetic tissue artifact of fast walking; (h) Synthetic tissue artifact of running.

Figure 4. Mutual information, mutual information ratio and power of the IMFs at SNR = 2 dB.

Figure 5.

SER results from EMD and LPF methods in Case 1. Percentage values represent the improvement of EMD-based technique over LPF.

Figure 6.

Examples of synthetic signals. Case 2: (a) $SNR = 4 \text{ dB}$, $f_{TA} = 0.40 \text{ Hz}$; (b) $SNR = 10 \text{ dB}$, $f_{TA} = 0.55 \text{ Hz}$; (c) $SNR = 16 \text{ dB}$, $f_{TA} = 0.70 \text{ Hz}$. Case 3: (d) $SNR = 14 \text{ dB}$, $f_{TA} = 1 \text{ Hz}$, $\theta_{TA} = 30^\circ$. Case 4: (e) slow walking; (f) fast walking; (g) running.

Figure 7.
Mutual information, mutual information ratio and power of the IMFs in case 3.

Figure 8.

Comparative results between “clean” respiratory signal and signal after tissue artifact removal. (Case 4 during fast walking). (a) Synthetic signal; (b) Comparative results with LPF; (c) Comparative results with EMD.

Table 1

SER Results from EMD and LPF Methods in Case 2

f_{TA} (Hz)	SNR = 4 dB		SNR = 10 dB		SNR = 16 dB		SNR = 22 dB	
	SER_{EMD}	SER_{LPF}	SER_{EMD}	SER_{LPF}	SER_{EMD}	SER_{LPF}	SER_{EMD}	SER_{LPF}
0.40	4.00	4.14	10.00	9.10	16.00	12.08	21.75	13.09
0.55	4.10	11.62	10.20	12.66	16.12	13.00	22.10	13.11
0.70	4.12	12.89	15.57	13.07	17.68	13.14	22.45	13.16
0.85	18.02	13.06	19.40	13.17	18.82	13.19	22.89	13.19

Table 2

Example of the Parameters of the Real Tissue Artifact Frequency Components of Running Activity

Parameter	Tissue Artifact Components ($N_{TA} = 41$)			
	Component 1	Component 2		Component 41
A_j (V)	0.01	0.01		0.02
f_j (Hz)	1.03	1.05		2.91
θ_j (rad)	-24.1π	-19.9π		-62.1π

Table 3

SER Results from EMD and LPF Methods in Case 4

Technique	SER (dB)		
	Slow walking	Fast walking	Running
EMD	15.13	15.09	18.26
LPF	13.00	13.38	13.06

Table 4

SER Results from EMD and DWT Methods in Case 3

Technique	SER (dB)
EMD	17.67
LPF	13.36
Haar	12.66
Daub2	13.95
Daub4	13.83
Daub10	13.53
Daub20	13.45

Table 5

Ventilation Estimation Comparison between EMD and LPF Methods

Method	Bias $\pm$ SD (l/min)	SE of Bias (l/min)	MPE (%)	RMSE (l/min)
EMD	-1.4 $\pm$ 10.1	0.9	12.4	9.8
LPF	-1.5 $\pm$ 11.3	1.1	14.6	10.9