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Employing Ensemble Empirical Mode Decomposition for Artifact Removal: Extracting Accurate Respiration Rates from ECG Data during Ambulatory Activity

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Abstract— **Observation of a patient's respiration signal can provide a clinician with the required information necessary to analyse a subject's wellbeing. Due to an increase in population number and the aging population demographic there is an increasing stress being placed on current healthcare systems. There is therefore a requirement for more of the rudimentary patient testing to be performed outside of the hospital environment. However due to the ambulatory nature of these recordings there is also a desire for a reduction in the number of sensors required to perform the required recording in order to be unobtrusive to the wearer, and also to use textile based systems for comfort. The extraction of a proxy for the respiration signal from a recorded electrocardiogram (ECG) signal has therefore received considerable interest from previous researchers. To allow for accurate measurements, currently employed methods rely on the availability of a clean artifact free ECG signal from which to extract the desired respiration signal. However, ambulatory recordings, made outside of the hospital-centric environment, are often corrupted with contaminating artifacts, the most degrading of which are due to subject motion. This paper presents the use of the ensemble empirical mode decomposition (EEMD) algorithm to aid in the extraction of the desired respiration signal. Two separate techniques are examined; 1) Extraction of the respiration signal directly from the noisy ECG 2) Removal of the artifact components relating to the subject movement allowing for the use of currently available respiration signal detection techniques. Results presented illustrate that the two proposed techniques provide significant improvements in the accuracy of the breaths per minute (BPM) metric when compared to the available true respiration signal. The error reduced from $\pm$ 5.9 BPM prior to the use of the two techniques to $\pm$ 2.9 and $\pm$ 3.3 BPM post processing using the EEMD algorithm techniques.**

I. INTRODUCTION

Respiration monitoring has long been an invaluable metric in the analysis and monitoring of a number of different chronic diseases, such as stroke and heart disease, as well as other ailments such as acute respiratory distress syndrome (ARDS). Over recent years, there has been an ever increasing move from hospital-centric healthcare towards in-home or ambulatory health assessment. This shift is in part due to the increasing financial burden on healthcare brought on by the increase in both population number and life expectancy. However, there remains a requirement for recording systems capable of providing quantitative assessment comparable to the gold standard results available in the hospital environment.

Currently there are systems available to provide high quality information regarding heart rate, respiration, movement etc. outside of the hospital environment however these systems often require multiple sensors which can be cumbersome to apply and can make the wearer uncomfortable. By doing so, the patient is more likely to act in an irregular manner and hence exhibit behaviour which may invalidate the results. There is therefore a desire to develop systems and sensors which can measure multiple vital signs concurrently and hence reduce the intrusiveness of the measurement.

Traditionally, respiration is measured using strain gauges or piezoelectric transducer devices strapped to the subjects chest or using air flow or pressure sensors on the subjects nasal cavity or mouth [1] [6]. Each of these sensors can cause discomfort to the user when used for prolonged periods. An alternative, more oblique respiratory measure can be accessed through appropriate processing of the ECG [4] however such techniques only perform well for ECG characterised by high signal-to-noise ratio (SNR). For example, the envelope detection method [7] (Section III-A) determines the respiration signal to be the variation in a spline connecting all the R-waves in the ECG. If the ECG signal is contaminated sufficiently with artifacts, this technique will no longer be able to provide the correct respiration signal.

This paper proposes a pre-processing method for deriving respiratory rate from ECG in the presence of contaminating artifact which would normally prohibit the accurate determination of the respiratory signal. The ensemble empirical mode decomposition (EEMD) technique is employed to test two separate methods for determining the respiration signal from these contaminated ECG signals. The first method uses the EEMD technique to separate the ECG signal into intrinsic mode functions (IMFs) and the IMF which best represents the respiration signal is then extracted. The second method differs by using the EEMD technique in conjunction with the available accelerometer signal to clean the ECG signal, allowing the standard envelope detection method to be used to determine the respiration signal. Both techniques are shown to significantly improve the accuracy of the respiration rate from contaminated ECG.

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Section II first describes the experimental setup including the data acquisition and experimental protocol adhered to. Section III describes the method for determining the respiration rate from the ECG and also describes the employed EEMD algorithm. Section IV provides the findings of the paper and finally Section V provides the overall conclusion.

II. Experimental Setup

This section summarises the basic experimental setup used to obtain the data utilised for this paper. For testing and validation, three separate data modalities are recorded: electrocardiography (ECG), acceleration and a reference respiration signal. The sensors used to monitor the required signals are first described below. Following this, the experimental procedure is presented.

A. Data Acquisition System

As already stated, three separate signal modalities were measured during the recording protocol. Figure 1 illustrates the "Smartex Wearable Wellness System (WWS)" chest strap [8] used to house the three recording sensors. This WWS is a wearable system based on textile knitted sensors [5]. The electrocardiography signal (ECG) is used to monitor the electrical activity associated with the pumping of the heart. The ECG signal was recorded using two moistened fabric sensors located at either side of the ribcage. The use of these fabric electrodes eliminates the requirement for adhesive electrodes which can be cumbersome to apply and have been shown to occasionally cause skin irritation [2], while also allowing for unlimited use. The ECG signal was recorded at a sampling rate of 250 Hz.

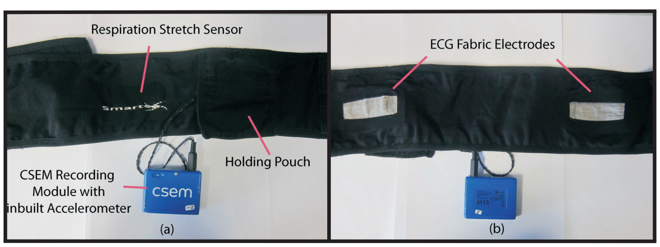

Fig. 1. Smartex Wearable Wellness System. (a) Respiration sensor positioned at the front centre of the band. Accelerometer located in the CSEM recording module which is housed in the indicated pouch. (b) Fabric ECG electrodes located on the inside of the chest strap.

The acceleration signal was recorded using a tri-axial accelerometer located in the recording module shown in Figure 1. This recording module was securely stored in the pouch located on the front of the chest strap and therefore the accelerometer could accurately monitor the positional changes of the body. The sampling rate of the accelerometer was set at 25 Hz.

The respiration signal was also monitored by a piezoresistive knitted textile sensor using the chest strap so that a reference signal was available against which the efficacy of the artifact removal techniques could be monitored. As stated in Section I, a proxy for the respiration signal can be determined from a recorded ECG signal. Therefore, by obtaining a true recording of the subject respiration rate, the deviation of the ECG derived respiration rate can be quantified. The respiration signal was recorded using a fabric stretch sensor located on the front sensor of the chest strap as can be seen from Figure 1. As the subject both inhales and exhales, the force on the stretch sensor alters, presenting a recordable change in resistance. This resistance change can then be related to the change in lung volume. The respiration sensor was also sampled at the lower frequency rate of 25 Hz.

All data recorded was stored on an on-board SD card for post processing using MATLAB ®.

B. Experimental Procedure

For the purpose of validating the proposed methodology and for determining a more accurate measure of respiration rate from an ECG signal, two separate recording protocols were employed. The first protocol (labeled Protocol 1) involved the recording of the three described signals while the subject slept. By performing this first protocol, the "best case" results can be determined for classification of the respiration rate from the ECG, when no motion artifacts are present. 2 hours of data was each recorded from 2 subjects (1 male, mean age 28 years).

The second recording protocol (labeled Protocol 2) involved the recording of the ECG, acceleration and respiration signals while the subject was in motion. In order to generate the required artifacts on the ECG signal, the subject was instructed to wear the chest strap while running outdoors. The presence of artifacts would degrade the quality of the ECG signal and thus make the classification of the respiration signal less accurate as can be seen from Table I. No specification was ordered on the pace of the individual runs. The cadence of the runs was determined to range from 75 to 95 revolutions per minute.

The determined respiration rates from the protocols described above are presented in Section III-A.

C. Data Setup

In order to test the efficacy of the described artifact removal technique, the data recorded using both protocols described in Section II-B were separated into individual epochs of 60 second duration. This data separation resulted in 120 trials of data for Protocol 1 and 29 trials for Protocol 2.

The 29 epochs of data from Protocol 2 were separated into training and test data to allow for the determination of the IMF component relating to respiration, as specified in Section III-B. 4 epochs were randomly selected as training data with the remaining 25 epochs used to test the efficacy of the techniques.

III. Methods

A. Deriving Respiration from ECG

As described in Section I there have been a number of different methods shown to be capable of determining subject respiration rate from ECG signals [7]. For the purpose of this paper the well known envelope method is used to establish the respiration rate. As stated previously, an ECG signal is a recording of the changing electrical activity of the heart recorded using electrodes on the chest. However, due to subject respiration the conducting volume of the body rhythmically changes. This volumetric change causes a low frequency signal fluctuation to be observed on the ECG and therefore by extracting this low frequency oscillation the respiration rate of the subject can be determined. The envelope method uses a cubic spline to connect the R-waves of the ECG, with the resulting spline representing the underlying respiration signal. Figure 2 shows an example of the envelope calculated over an epoch of clean data from Protocol 1. The correlation with the corresponding respiration signal can be easily observed.

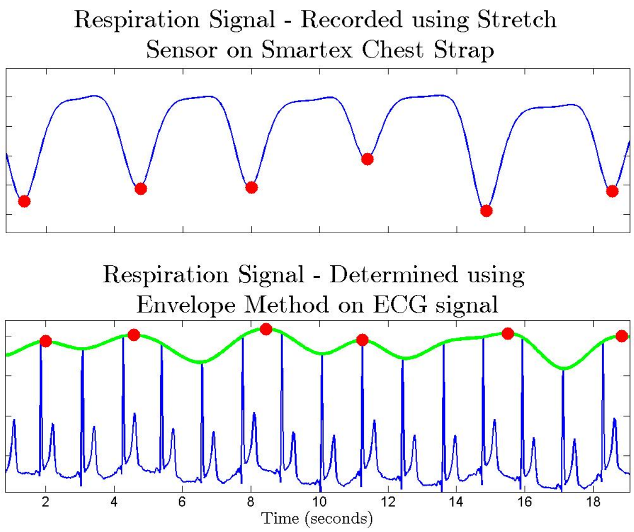

Fig. 2. Envelope detection for determining the respiration rate from an ECG signal.

However, with the data recorded using Protocol 2, the artifact due to motion has contaminated the ECG disrupting the amplitude of the R waves. Therefore the envelope method does not function as optimally as before. It is therefore desirable to remove the contaminating artifact so as to improve the performance of the envelope method.

Prior to running the artifact removal techniques the respiration rates of the true respiration signal and the respiration rate determined from the ECG, recorded using Protocols 1 and 2, were calculated. Protocol 1 resulted in an average respiration rate of 14.8 breaths per minute (BPM) with the ECG derived respiration having a deviation of ± 1 BPM, similar to those results shown in [1]. For Protocol 2 the true average BPM was 50 BPM and the calculated deviation of the ECG derived respiration was much larger at ± 5.9 BPM due to the presence of the artifacts.

B. *Ensemble Empirical Mode Decomposition*

Empirical mode decomposition (EMD) is a method, first defined in 1998 [3], for nonlinear signal processing and is well suited to non-stationary signals. The method decomposes a time series signal into multiple "intrinsic mode functions" (IMFs). The EMD technique differs from other techniques [9], such as Wavelet analysis, in that the decomposition of the signal is data driven whereas wavelet analysis relies on the selection of the appropriate wavelet. As the technique is data driven, it is therefore adaptive in nature, making it very flexible.

The IMFs are functions that satisfy two separate conditions: (1) over the full length of the data set the number of maxima and the number of zero crossings must be the same or differ at most by one and (2) at any point over the data set, the mean value of the envelope defined by the maxima and the envelope defined by the minima must be zero [3]. The interested reader can find the steps performed to determine the underlying IMF in [10]. The EMD algorithm is however very sensitive to noise in the recorded signal. This can lead to complications due to mode mixing. Mode mixing is defined as an IMF that includes oscillations of dramatically disparate scales or a component of similar scale residing in different IMFs, and can also be due to the presence of a transient spectral component in the signal. An extension to the EMD algorithm was proposed in [10] which eliminates this mode mixing problem. The updated algorithm called Ensemble-EMD (EEMD) uses an average of a number of ensembles of the EMD algorithm as the optimum choice of IMFs. Each run of the EMD algorithm has an independent, identically distributed white noise of the same standard deviation added thus providing a noise-assisted data analysis method.

For the purpose of this paper, the EEMD technique was employed in two separate approaches. The first approach (labeled Approach 1) used the EEMD algorithm to decompose the signal into its IMFs with the expectation that one of the IMF would itself represent the respiration signal. This is expected as the respiration signal will have the same number of maxima as minima while having a zero mean. The second approach (labeled Approach 2) again employed the EEMD to decompose the ECG signal, but in this instance the component(s) relating to the movement artifacts were removed and the cleaned ECG signal was then reconstructed. The respiration signal could then be calculated using the steps described in Section III-A.

Approach 1 requires the component relating to the respiration signal be determined. This optimal IMF component was first determined using the 4 training trials and the corresponding true respiration signal. The component relating to respiration was determined to be the IMF which had the maximum correlation with the corresponding true respiration signal. This IMF component was then determined to also represent the respiration signal for the test data.

Approach 2 employed the available accelerometer signal to determine the contaminating artifact signal IMF. The accelerometer outputs are related to the movement of the subject and thus can be assumed to be correlated with the artifact signal contaminating the ECG signal. Therefore by removing the IMF components which are most correlated with the accelerometer output, the power of the contaminating artifact on the reconstructed ECG signal is reduced allowing for a more accurate classification of the respiration rate using the envelope method.

IV. RESULTS & DISCUSSION

The two different EEMD approaches described in Section III-B were run on the 25 individual trials of test data from Protocol 2. For both EEMD techniques, the number of ensembles was set to 5 and the standard deviation of the noise was set as 0.2. The resulting respiration rate in breaths per minute (BPM) was determined after applying both Approach 1 & 2. Each trial was re-run 100 times to retrieve an average result for each trial. This was required as the determined IMF can vary slightly with each run due to the variability in the added noise. Table I presents the obtained results. The results show the true average BPM value (obtained using the stretch sensor located on the chest strap) and the average difference in BPM of the original ECG signal and after applying Approach 1 & 2.

TABLE I
IMPROVEMENT IN CALCULATED BPM AFTER USING THE EEMD TECHNIQUES.

	Respiration	ECG	EEMD App. 1	EEMD App. 2
BPM	50	$\pm$ 5.9	$\pm$ 2.9	$\pm$ 3.3

The results presented above validate that the EEMD techniques significantly improve the accuracy of the respiration rate estimate derived from the artifact contaminated ECG. These results show on average a 51 % reduction in error when applying Approach 1 (selection of the respiration signal from the IMF) and a 44.1 % reduction when using Approach 2 (using the accelerometer signal to determine the artifact IMF components prior to the reconstruction of the signal and the calculation of the respiration using the envelope method). The greater performance improvement, using Approach 1, could be due to the EEMD's ability to more accurately separate the respiration component, rather than the artifact components, from the noisy ECG.

Although providing slightly lower results, Approach 2 is adaptive in nature allowing it to function similarly even if the respiration rate or the running pace changes. Approach 1 provides quantitatively better results, however the method is not amenable to real-time automatic estimation. To allow the technique to operate automatically, an algorithm capable of determining which IMF component relates to the respiration signal would be required to be developed.

V. CONCLUSION AND FUTURE WORK

Respiration monitoring is a clinically useful measurement which can be used to aid in the diagnosis and treatment of a number of different ailments. As some of the monitoring systems are uncomfortable to wear for long durations or require the use of additional sensors they are rarely used outside of the hospital environment. However, the respiration signal can also be determined using an ECG signal recording allowing for the monitoring of multiple vital signs using a single sensor, thus reducing hardware complexity and the power required by the implemented systems. Further, the utilised ECG textile electrodes are low cost and are widely available (e.g. Polar WearLink ®, Adidas miCoach ®). Unfortunately, methods used to determine the respiration rate from ECG signals are prone to artifacts, and their accuracy can be reduced significantly. In this paper we examined the use of the ensemble empirical mode decomposition (EEMD) algorithm to determine a more accurate representation of the respiration rate.

Two separate approaches were analysed. Approach 1 separated the artifact contaminated ECG signal into its corresponding IMF, and through previous training, selected the IMF relating to the respiration signal. This approach functioned well, however its inability to adapt to large variations in respiration rates and the requirement for training prior to application may restrict its use in on-line systems.

Approach 2 used the accompanying accelerometer signal to determine the IMF components that were related to the motion artifact. These IMF were then removed prior to the reconstruction of the cleaned ECG signal where the envelope method was used to determine the respiration rate of the signal. This technique is adaptive and will operate with varying BPM, however it will encounter problems if the frequency of the accelerometers matches that of the respiration signal.

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