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Development of three methods for extracting respiration from the surface ECG: A review

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Abstract

Background: Respiration rate (RR) is a critical vital sign that can be monitored to detect acute changes in patient condition (e.g., apnea) and potentially provide an early warning of impending life-threatening deterioration. Monitoring respiration signals is also critical for detecting sleep disordered breathing such as sleep apnea. Additionally, analyzing a respiration signal can enhance the quality of medical images by gating image acquisition based on the same phase of the patient's respiratory cycle. Although many methods exist for measuring respiration, in this review we focus on three ECG-derived respiration techniques we developed to obtain respiration from an ECG signal.

Methods: The first step in all three techniques is to analyze the ECG to detect beat locations and classify them. 1) The EDR method is based on analyzing the heart axis shift due to respiration. In our method, one respiration waveform value is calculated for each normal QRS complex by measuring the peak to QRS trough amplitude. Compared to other similar EDR techniques, this method does not need removal of baseline wander from the ECG signal. 2) The RSA method uses instantaneous heart rate variability to derive a respiratory signal. It is based on the observed respiratory sinus arrhythmia governed by baroreflex sensitivity. 3) Our EMGDR method for computing a respiratory waveform uses measurement of electromyogram (EMG) activity created by respiratory effort of the intercostal muscles and diaphragm. The ECG signal is high-pass filtered and processed to reduce ECG components and accentuate the EMG signal before applying RMS and smoothing.

Results: Over the last five years, we have performed six studies using the above methods: 1) In 1907 sleep lab patients with >1.5 M 30-second epochs, EDR achieved an apnea detection accuracy of 79%. 2) In 24 adult polysomnograms, use of EDR and chest belts for RR computation was compared to airflow RR; mean RR error was EDR: 1.8 ± 2.7 and belts: 0.8 ± 2.1. 3) During cardiac MRI, a comparison of EMGDR breath locations to the reference abdominal belt signal yielded sensitivity/PPV of 94/95%. 4) Another comparison study for breath detection during MRI yielded sensitivity/PPV pairs of EDR: 99/97, RSA: 79/78, and EMGDR: 89/86%. 5) We tested EMGDR performance in the presence of simulated respiratory disease using CPAP to produce PEEP. For 10 patients, no false breath waveforms were generated with mild PEEP, but they appeared in 2 subjects at high PEEP. 6) A patient monitoring study compared RR computation from EDR to impedance-derived RR, and showed that EDR provides a near equivalent RR measurement with reduced hardware circuitry requirements.

Keywords: ECG derived respiration; Respiratory sinus arrhythmia derived respiration; EMG derived respiration; Respiration gating; Sleep apnea detection

Introduction

The derived signals and measurements from respiration have many applications in medicine and healthcare. Respiration rate (RR) is a critical vital sign that can be monitored to detect both subtle and acute changes in patient condition (e.g., apnea) and potentially provide an early warning of impending life-threatening deterioration, e.g., sepsis or respiratory depression in post-surgical patients receiving patient-controlled analgesia. Both its absolute value and changes in rate are markers of illness and predictors of serious clinical events. The respiratory signal

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and derived rate are used extensively in patient monitoring throughout the hospital in low to high acuity clinical units, where the rate is charted, monitored, and used for alarm generation and where the derived respiratory signal from the diaphragm may be used for acute-care ventilator triggering [1]. Outside the hospital setting, respiration monitoring plays an important role in EMS care and resuscitation. It can be used to detect sleep apnea and other sleep disordered breathing patterns as part of polysomnography in sleep clinics or at home. One application which might not immediately come to mind is in signal gating applications where it is used to remove or compensate for the effects of respiratory motion of the thoracic organs; both ECG and respiration are used for image gating and stabilization in CT, MRI, and PET/SPECT nuclear imaging [2]. The respiration signal also has uses in improving diagnostic [3] and high-resolution ECG applications (e.g., T-wave alternans detection), where removing respiration's modulating effects on the ECG may improve diagnostic accuracy [4].

An overview of respiration acquisition methods

There are many respiration acquisition methods, starting with those that do not physically contact the person. Video camera methods run the gamut ranging from high-end expensive camera systems that track bright objects placed on the chest and used in CT image gating, to low-cost vital signs "apps" for mobile devices that give heart rate by detecting facial flushing with each beat and respiration rate by chest movement [5]. Thermal cameras detect air movement and temperature effects, while radar and Wi-Fi disturbance methods detect chest wall motion [6,7].

The second class of methods requires physical contact with a person. The respiratory impedance method is commonly used in many medical devices such as patient monitors, where specialized circuitry detects changes in a low-voltage, high-frequency oscillating signal sourced and measured through ECG electrodes without using the ECG signal itself. Inductance-changing and strain gauge belts placed around the thorax and abdomen are widely used for CT and MRI image gating, as well as sleep monitoring. Both airflow and CO_2 sensors used in-line with oral airway devices (e.g., endotracheal intubation tubes), as well as CO_2, acoustic, and thermal sensors placed near the nasal airway or in nasal cannulas are used for respiration monitoring in a variety of applications. Although they have not yet become a standard of care, there is research being done to extract ECG and respiration with conductive clothing and bed sheet textiles [8]. Accelerometers in small, wireless, patches placed on the thorax that detect chest wall movement are now being used in patient monitoring systems to provide respiration rate. Esophageal electrical probes passing through the diaphragm have been productized for use in ventilator triggering using diaphragmatic EMG [1].

Since ECG is routinely monitored in many settings, researchers have also pursued methods for extracting respiration signals directly from the acquired ECG waveform. In this paper we will review our research group's three previously developed ECG-derived methods and summarize their past and present testing results. Algorithm details of our EMG-based method that have not been previously published will be presented.

Three ECG-derived respiration methods

The three ECG-derived methods we have implemented and tested to compute a respiration signal are: (1) "EDR" based on changes in the ECG vector projection, (2) "RSA" based on respiratory sinus arrhythmia, and (3) "EMGDR" based on muscle electromyogram activity. All ECG-derived methods have the advantage over other techniques in many settings where ECG is routinely acquired: they can be added without additional hardware such as that needed for impedance circuitry, cumbersome belts, or expensive video solutions. The respiratory signals produced by these methods may be used by secondary algorithms to detect breaths, trigger gating methods, compute respiration rates, or detect episodes of sleep disordered breathing.

The methods presented below require only one individual ECG lead, but are suitable for combination in multi-channel algorithms. The EDR and RSA methods may be implemented using typical "monitoring" bandwidths and sample rates (e.g., 0.5–40 Hz, ~100sps), but the EMGDR method requires higher ECG bandwidth (ideally with high end up at 500 Hz with minimum 1000sps).

Method 1: "EDR": ECG-derived respiration

Our EDR method is based on QRS axis shifts that are produced by changing cardiac vector projections onto a changing electrode geometry which occur when the lungs are filled with air. During respiration, many things happen at once that affect the ECG: the heart, which is physically anchored by the vessels on one end and rests on top of the diaphragm, rotates in multiple dimensions; the heart-to-electrode distances change during thoracic expansion; and, secondarily, the ECG is affected by changes in thoracic impedance as air fills spaces in the lungs. These factors create a modulating effect on the ECG related to the respiratory cycle. The approach to use the modulating QRS morphology for respiration extraction was first published by Moody et al. in 1985 [9]. The original techniques used the changes in QRS area in two orthogonal leads. We recently enhanced the approach with an algorithm simplification that uses the easily measurable total (peak-to-trough) QRS amplitude in a single lead, and thus does not require the calculation of QRS area or accurate baseline detection and removal [10].

The first step in our EDR algorithm is to detect beats with a QRS detector. We then measure the total QRS amplitude as shown in Fig. 1. Outlying values greater than two standard deviations from the running mean (e.g., artifact) are discarded. The QRS amplitude is used as the respiration signal amplitude at the time of each beat, as shown by the circles on the lower plot in Fig. 1. Cubic spline

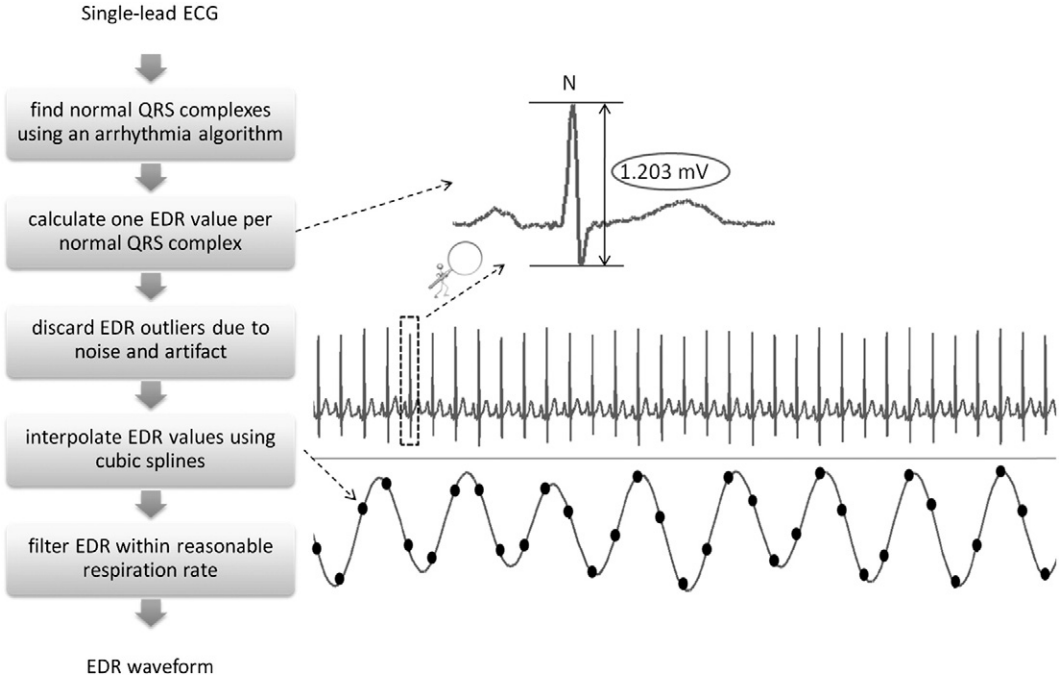

Fig. 1. Sequential steps used for derivation of the EDR (ECG-derived respiration) signal from single-lead ECG. Peak-to-trough QRS amplitude (EDR value) is measured for each normal QRS complex. Outlying EDR values (>2 standard deviations from the mean) are excluded. EDR values are then interpolated using cubic splines and the interpolated EDR signal is filtered within application-based expected respiration rates to retain the main respiratory component.

interpolation is used to produce the continuous EDR respiration waveform. Finally, the waveform is filtered with a band-pass filter as suited for the range of rates expected in the application setting.

An advantage of the EDR method is that QRS detection and measurement are relatively resistant to muscle artifact. We have shown it has good potential for MRI image gating in the presence of MRI interference [11]. The amplitude displacement due to chest movement, which is the basis for EDR, shows good correlation to tidal volume. This potentially makes EDR suitable for detecting central apnea episodes.

A drawback of the EDR method is that it may miss obstructive apnea episodes if QRS axis shift occurs due to respiratory effort and chest movement but without airflow. Another potential disadvantage is that the derived respiratory signal phase may not match that of tidal volume, that is, peak EDR may not correspond with peak tidal volume, and could potentially occur 180 degrees out of phase. We hypothesize that the correlation is likely lead dependent, and additional research is needed to explore the phase relationships as a function of lead placement and pairing. Another disadvantage for some applications is that the respiratory wave samples are available only at QRS times, and thus the signal may be under-sampled if the heart rate (HR) is low or respiration rate is high; it is dependent on the cubic-spline interpolation to create the minimum and maximum amplitudes and locations. Frequent ectopic beats will further reduce the respiration signal sampling; however, scaled amplitude measurement of frequent monomorphic ectopic beats could potentially be added to the algorithm to improve performance in this situation.

Method 2: "RSA": respiratory sinus arrhythmia derived respiration

The second method we have implemented and tested uses instantaneous heart rate (IHR) variability known as respiratory sinus arrhythmia. Previously we reported on our heart-rate variability (HRV) frequency-domain method to detect sleep apneas from rising and falling HR cycles [12], but this time-domain method can be used to produce an actual respiratory waveform. It is based on the observed respiratory sinus arrhythmia governed by baroreflex sensitivity, where receptors in the main and peripheral arteries respond to slight pressure changes created by breathing. Usually, IHR increases during inspiration and drops during expiration with very fast response times, a well-known and thoroughly studied subject [13,14]. In this method, as illustrated in Fig. 2, we use each QRS complex R-R interval in the ECG to calculate IHR (the inverse of R-R), and then use the IHR value as the respiration wave amplitude at each beat, as shown by the height of the arrows (Fig. 2d). Using HR rather than R-R inverts the signal to have peaks at end-inspiration and valleys at end-expiration and thus better match the points of maximum and minimum tidal volume. We then use cubic spline interpolation to produce the final respiratory waveform (Fig. 2c).

One advantage of the RSA method is that only the QRS locations are needed whose detection is fairly resistant to muscle artifact and MRI interference. However, the disadvantages of this method are many in all but a few applications (e.g., where young, healthy patients are quietly resting). The underlying premise of this method often breaks down, for example, when respiration-induced RSA has naturally decreased with age or illness, when there are supra-ventricular or

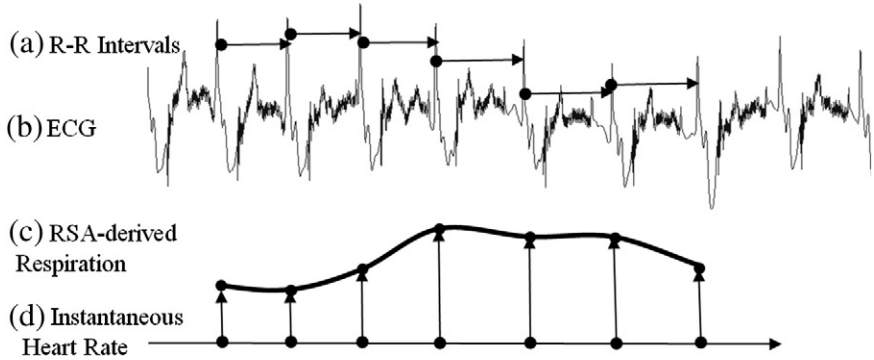

Fig. 2. RSA-derived respiration: Varying R-R intervals (a) (horizontal arrows) from QRS detections on the ECG (b) are computed. The inverse of the R-Rs (d) (vertical arrows, exaggerated for illustration), computed as instantaneous heart rate, are used as amplitude knots for cubic spline interpolation to create the RSA-derived respiration waveform (c).

ventricular arrhythmias, or when patients are on rhythm- and rate-control medications or devices. There are varying phase delays of IHR compared to tidal volume (e.g., 2–7 seconds [14]) in response to sudden changes in breathing patterns, as well as factors affecting HR (e.g., changes in position, movement/exercise, or sleep disordered breathing) which would prevent IHR from being used in the RSA method to accurately reflect only respiration and ventilation volume. As with EDR, respiratory wave samples are available only at QRS times, and thus the respiratory signal may be under-sampled and highly dependent on the accuracy of the cubic spline.

Method 3: "EMGDR": electromyogram derived respiration

Our third method is based on extraction and processing of the electromyogram (EMG) signal from the ECG. Our development of this method (led by A. Dean Forbes, HP Labs, retired) in the 1990's [15] was first inspired by our observation of periodic bursts of high-frequency muscle noise visible in some 12-lead ECGs. (Willem Einthoven, in fact, had observed this as early as 1913 [16].) The EMG method premise is that ECG recordings will contain muscle tremor "noise" from electrical activation of the inter-costal chest muscles and the diaphragm during the respiratory cycle (Fig. 3a). This EMG signal is from muscle motor units activated by the central nervous system and is superimposed on the cardiac ECG signal. In our experience, the respiratory EMG is best found in the frequency band above 250 Hz (Fig. 3b). The running power of this EMG corresponds to respiratory "effort" and can be used to compute a continuous respiratory waveform (Fig. 3e) with upslope corresponding to inspiration and with downslope corresponding to expiration and with a peak at end-expiration.

Our EMGDR algorithm is as follows: since we have found the EMG to have a center frequency between 250 and 500 Hz, we start with 1000sps ECG with bandwidth up to 500 Hz. We then high pass filter at 250 Hz which accentuates the EMG and removes much of the lower frequency cardiac components such as P and T waves (Fig. 3b), although the high-frequency components of the QRS remain as spikes. To capture the "power" of the muscle activity we compute the root mean square (RMS) of the signal in a 51 millisecond sliding window that slides forward by one sample at a time. In this application, the RMS is equivalent to the standard deviation of the EMG since the 250 Hz high-passed signal has a mean of zero. The location of the center point of the 51 millisecond sliding window is used as the location of the output RMS value, so that signal delays are not introduced. This gives the RMS signal (Fig. 3c), which appropriately rises above the baseline as the EMG increases during inspiration (as shown by the arrows). To remove the unwanted residual QRS artifact (namely the spikes such as the one highlighted in the oval) we run a QRS detector on the original ECG and find QRS onset and offset, and then use linear interpolation over the QRS width in the RMS waveform to chop out the residual QRS spikes, as shown in the ovals, before and after. This results in the signal which now looks much more like a pure respiration waveform (Fig. 3d). Our final step is to use a simple moving average (SMA) filter (which is the signal mean in a sliding window) to low-pass smooth the jagged RMS waveform into the final EMGDR respiration signal (Fig. 3e). This last process employs a sliding averaging window which also uses a symmetric window around a center point whose location is used as the location of the final output. Since respiration has a much lower bandwidth than ECG, a lower sample rate for respiration can efficiently be obtained by shifting the SMA averaging window by more than one sample point at the completion of each iteration, such as by 8 points to obtain decimation from 1000sps to 125sps.

Occasionally we have observed that either some cardiac signal artifact remains in the EMGDR respiratory signal, or non-physiologic perturbations are introduced from the linear interpolation method used to remove the cardiac artifact. A novel approach to remove any remaining cardiac residuals or perturbations at the beat locations is to set the SMA filter averaging window length equal to the corresponding ECG R-R interval to effectively notch filter the signal at the cardiac frequency [17]. It is a known characteristic that if you set the width of the averaging interval equal to the length a certain frequency, the frequency response will be 0 at that frequency. For example, if the HR is 60, which is a beat occurring at 1 Hz, and you use a window length equal to the

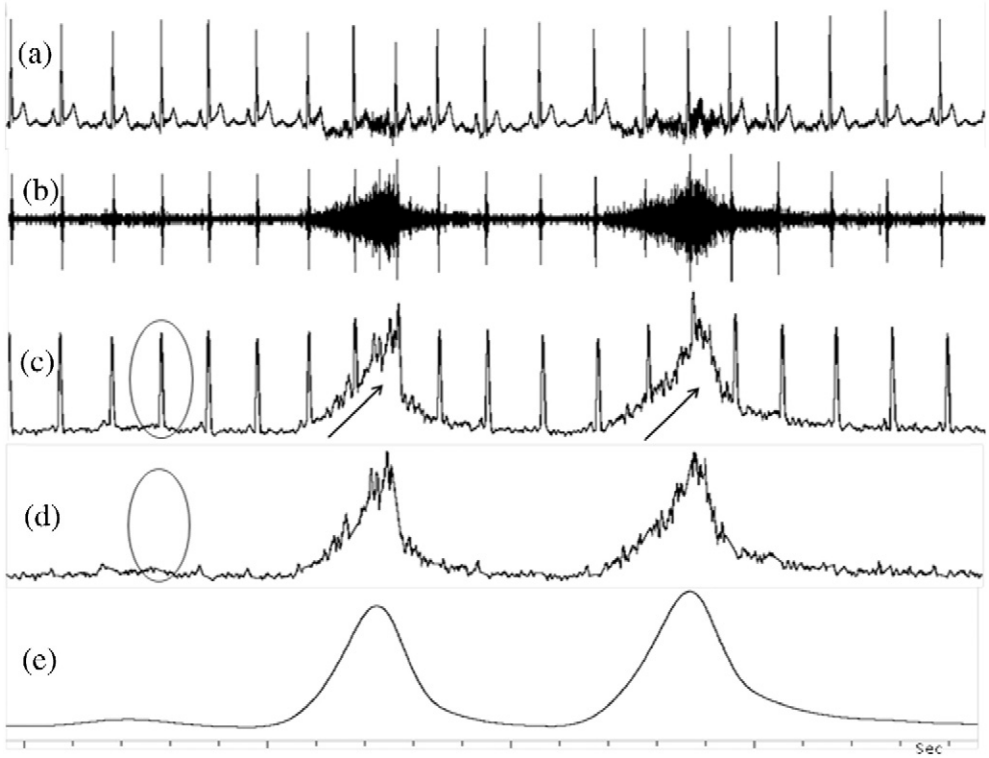

Fig. 3. Sequential waveform output from each step used for the computation of electromyogram-derived respiration (EMGDR). (a) Raw 1000sps ECG with bandwidth up to 500 Hz; muscle "artifact" from 2 breaths can be seen. (b) Output from 250 Hz high-pass filter; residual QRS energy is still present. (c) RMS is computed in 51 millisecond sliding windows; the signal baseline increases during each breath (arrows); residual QRS energy is still present (oval). (d) Residual QRS energy is removed (e.g., oval) by linear interpolation on the RMS signal over the QRS onset and offset, as determined by a QRS detector. (e) Final EMGDR respiration signal created as output from an adaptive varying-width simple moving average filter. To remove any remaining cardiac perturbations, the width of the filter is set to the cardiac R-R interval creating a notch filter, and adjusts in a linear fashion as its center moves from beat to beat.

cardiac R-R interval which is one second, you have a notch in the filter at 1 Hz. This will remove much of the events/artifact occurring at the cardiac HR frequency, even though these event artifacts are not actually a sine wave at 1 Hz. Respiration rate is often less than heart rate by a factor of four or more, so respiration passes through but the higher cardiac event frequencies are attenuated. One implementation issue with this approach is that the cardiac R-R interval is not constant; we overcome this by adaptively adjusting the notch frequency as we move from one beat to the next while we are computing the respiratory signal. We start by setting the width of the SMA averaging window equal to the current cardiac R-R interval. We use center of the window as the output location. We then linearly adjust the window width as the window center travels forward in the sliding process to meet the center of the next cardiac R-R interval. Thus, the averaging interval grows and shrinks in small steps as we move from one beat to the next. The output of this adaptively varying SMA filter is used as the final fully-processed EMGDR respiratory signal.

It was only after we had developed and tested our EMGDR method and with the advent of more comprehensive internet search engines that we found prior work using techniques similar to ours. In 1961, Stephenson [18] used an EMG-derived respiratory signal from needle electrodes in the chest for ventilator triggering. This technique was also pursued by groups in the late 1990's including Van Eykern in the Netherlands [19] and Sinderby of Canada [1] who productized the approach for Maquet using an invasive esophageal electrode catheter for diaphragmatic EMG acquisition. Used for ventilator control, the method was named "NAVA" for neurally adjusted ventilatory assist.

In our EMGDR testing, patient movement of limbs and torso, as expected, can generate additional EMG signals that become superimposed on the ECG and create large excursions in the EMGDR signal which appear as large breaths. For this reason, the technique is best suited for applications when the patient is at rest. We have looked at the correspondence of the EMG respiration signal with the current standard impedance method. In resting subjects, we usually find good correlation between the two, not only for breath locations but often for amplitudes, as less muscle activity is used for smaller breaths. EMGDR also correlated well with simultaneous tidal volume measurements from a flow pneumotach, with peak EMGDR signal amplitudes occurring at the time of maximum tidal volume and similar trends in amplitude between the two techniques. It appears that peak EMG occurs at end-inspiration, and that the EMG decays rather than completely cuts off when full inspiratory volume is reached; the exploration of the phase difference, if any, between EMGDR and tidal volume, however, needs more thorough investigation and testing.

We have tested the EMGDR method on a number of cases taken during MRI cardiac imaging [11,20]. The MRI environment creates a significant amount of high-frequency energy on the ECG from the field gradients when the scanner

is scanning. When we used the EMGDR method on these waveforms, the baseline of the derived respiration signal rose in a manner similar to a large step function when scanning was initiated, but the respiration signal (as confirmed with inductive stretch belts) was still clearly visible riding on top of this raised baseline from the underlying MRI interference. When the periodic cardiac scanning occurs based on ECG triggering for each beat, the low-pass averaging filtering in the EMGDR method smoothes out the cardiac-gated MRI gradient "noise" to create a constant level baseline value. The one difficulty we encountered was when scanning of a beat was suspended when there was an atrial premature contraction; in this case, the sudden cessation of the MRI interference caused a sudden drop in the EMGDR signal, which could provide difficulty for a subsequent breath detection algorithm to interpret. Additional development work in this area is needed to be able to effectively create a respiratory signal in the presence of beats which do not trigger the cardiac-gated MRI scanning process, such as atrial and ventricular premature beats.

One advantage of the EMG method is that it has a similar respiratory phase with both impedance and tidal volume. It also reflects respiratory "effort", a measurement not available with other methods, and thus has potential for use in applications like ventilator triggering. A disadvantage is that it ideally requires ECG with a high-frequency bandwidth; however, the algorithm was still able to produce good respiratory signals from ECG signals with a lower low-pass filter cutoff such as diagnostic 12-lead ECGs with 150 Hz low-pass filters, since most low-pass filters are not ideal and still allow much of the EMG signal through. Anecdotal performance on 12-lead diagnostic ECGs is that we could compute EMGDR from each lead with good correspondence across a majority of leads on approximately 80% of cases. A major drawback that may limit the method's use in ambulatory patients is that it suffers a performance loss in the presence of muscle artifact from movement, which creates non-respiratory peaks in the signal [21], but the method has potential for respiration monitoring during sleep when patient movement is reduced. Previously we have reported the potential for creation of false-positive breaths which may limit the method's use in the presence of advanced respiratory disease like COPD and asthma where muscles are recruited during the final period of *expiration* to force air out of the lungs against intrinsic positive end-expiratory pressure (PEEP) [22]. Finally since the EMGDR method reflects respiratory effort and not always tidal volume, it could be used to detect central apneas but possibly may not be suitable for use in detecting episodes of obstructive sleep apnea where respiratory efforts are made but there is no airflow.

We have identified three possible directions for future EMGDR development and testing: 1) to independently detect intercostal and diaphragmatic EMG activity; when these become out of phase it is indicative of increased respiratory load; 2) to non-invasively detect diaphragmatic activity from the chest surface with comparable performance to invasive esophageal electrode probes (e.g., used for NAVA) for ventilator triggering, but with less chance of infection; and 3) to detect left and right diaphragm activity independently, which would allow, among other things, assessment of inadvertent surgical damage to the left or right phrenic nerve, which is occasionally a surgical complication. An area of investigation that could form the basis of this work would be to explore optimal electrode positions and lead-to-lead or lead-to-central-terminal subtractions to provide the best signals for accomplishing the goals.

Results

We conducted six evaluation studies of our three ECG-derived respiration signal methods:

(1) On polysomnogram (PSG) data from 1907 sleep-lab patients containing over 1.5 million 30-second epochs, an algorithm analyzing the EDR waveform classified 96% of the epochs as normal or SDB (and not indeterminate) with an accuracy of 79%. When used in conjunction with a previously developed HRV frequency-domain method, 78% of epochs could be classified with an accuracy of 88% on those epochs [10].

(2) We recently performed a study to test the EDR method for computing respiration rate during polysomnogram sleep studies [23]. In this study, evaluation was done on 24 adult PSGs from the publicly available PhysioNet ucddb database. Subjects were randomly selected from patients referred to a sleep lab for possible diagnosis of sleep apnea. Subjects had no known cardiac disease, autonomic dysfunction, and were not on medication known to interfere with heart rate. In order to detect the normal QRS complexes and remove the abnormal ones, ECG was automatically analyzed using the Philips ST/AR QRS detection and beat classification algorithm. The EDR waveform was then constructed by measuring the peak to trough amplitude in each normal QRS complex, and interpolating the measurements using cubic splines, as described earlier. A frequency-domain method was developed to calculate respiration rate in a 30-second sliding window with a 5-second step by finding the fundamental frequency of oscillations. This method was applied to all four waveforms: airflow, EDR, ribcage, and abdominal belts. The RR values computed from airflow, used as reference, were compared with RRs from the other waveforms. A total of 119,698 respiration cycles were analyzed. The average difference in RR from airflow was 0.7 ± 1.8 breaths-per-minute (bpm) for abdominal belt, 1.0 ± 2.4 for ribcage belt, and 1.8 ± 2.7 for EDR. The difference in RR from abdominal belt, ribcage belt, and EDR compared to airflow RR was within 1 bpm for 86%, 83%, and 63% of the cycles respectively, and within 3 bpm for 94%, 92%, and 81% of the cycles.

(3) During cardiac MRI, a comparison of EMGDR breath locations to the reference abdominal belt signal using manually annotated breath identifications yielded a sensitivity of 94% and positive predictive value of 95% [20].
(4) Another comparison study for breath detection during cardiac MRI to the reference abdominal belt, this time using an automated breath detection algorithm on all respiratory signals, yielded sensitivity/PPV pairs of EDR: 99%/97%, RSA: 79%/78%, and EMGDR: 89%/86% [11].
(5) We tested EMGDR performance in the presence of simulated respiratory disease (COPD) using CPAP to produce PEEP (positive end-expiratory pressure). For 10 patients, no false breath waveforms were generated with mild PEEP, but they appeared in 2 subjects at high PEEP [22].
(6) An in-hospital patient-monitoring study we recently completed compared RR computation from both impedance and EDR, and showed they had similar performance in average respiration rate computation, with a mean difference of 2 ± 3.5 bpm. Additional studies are needed with gold-standard annotations e.g., from ventilator or airway CO_2 sensor breath location identifications.

Conclusion

Three methods for computing a respiration waveform from the ECG have been developed with potential applications in numerous medical settings. It is unlikely that ECG-derived methods will ever be as accurate as using an airway airflow sensor. However, we achieved fairly good performance with many performance measures generally in the 80 to high 90% levels, but without the need for hardware additional to that for ECG acquisition. Each method has pros and cons for different applications. It may be possible to improve the overall performance by combining the different methods.

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