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Research Article

A Comparative approach to ascertain respiratory parameters from single channel ECG

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ABSTRACT

Respiration rate is a crucial parameter for monitoring respiratory health. This study analyses and compares various techniques for estimating respiration rate from electrocardiogram (ECG) signals. Multiple approaches for calculating single-lead ECG-derived respiration (EDR) were investigated under diverse conditions, including baseline wander, different recording devices, and various breathing patterns. A reference respiratory signal was used to evaluate the accuracy of each method. The results show that the phase space reconstruction area method outperformed other state-of-the-art approaches, achieving the maximum mean correlation. This method demonstrated high accuracy and reliability in estimating respiration rate from ECG signals. The study provides a comprehensive review and comparative analysis of various techniques for estimating respiration rate from ECG signals. The findings suggest that the phase space reconstruction area method is the most accurate and reliable approach, making it a valuable tool for healthcare monitoring applications. This method has significant potential for monitoring respiratory health, particularly in situations where traditional respiratory monitoring methods are impractical or unreliable.

Keywords: Respiration Rate, ECG Derived Respiration (EDR), New Complementary Empirical Ensemble Mode Decomposition, Phase space reconstruction area, Hermite expansion

INTRODUCTION

In essence, the human body is a complex fusion of several physiological systems. These systems are interdependent and interrelated. Breathing generally influences heart rate due to the link and interactions between the cardio-respiratory systems. This can be accomplished by employing signal processing techniques to extract breathing and heart rate information from the electrocardiogram (ECG) signals. Respiration is the process by which O_2 is transported from the ambient air to the cells that make up tissues, and CO_2 is expelled. 500 millilitres of air are inspired or inhaled. Figure 1 illustrates the resting airflow rate, which ranges between 5 and 8 litres per minute (Zakeri et al., 2016).

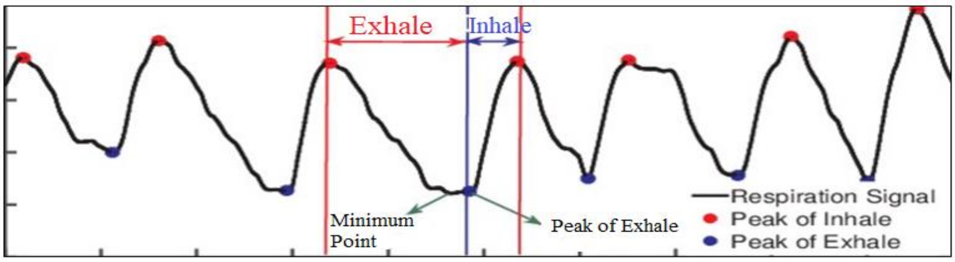

Figure 1: Normal Respiratory Pattern (Zakeri et al., 2016)

A person's respiration rate is the most significant indicator of their respiratory health. One can determine their breathing rate by measuring the number of rises and falls in the chest per minute. Table 1 displays the range of breathing rates for a healthy individual (Gao et al., 2012).

Table 1: Normal Ranges of breathing rates (Gao et al., 2012)

Age	Respiratory Rate (Breath Per Minute)
New Born	30-60
Toddler (1 to 12 months)	30-60
Young Children (3-5 years)	22-34
School-age child (6-12 years)	18-30
Teenage (13-17 years)	12-16
Adult	12-18

Traditional methods like spirometers and pneumotachometers are ineffective during sleep or periods of high exertion, but indirect approaches like plethysmography and pneumography record breathing signals (Du and Jose, 2017). These methods can track cardiorespiratory function and are practical and reasonably priced. ECG-derived respiration techniques have been used in some studies to precisely extract breathing signals from a single lead ECG (Bailón et al., 2006).

The ECG-Derived Respiration (EDR) technique is based on the discovery that differences in heart and transthoracic impedance correspond to changes in the placements of ECG electrodes on the chest's surface when the lungs are full and empty (Apsara et al., 2017). Because of this, the lead axes change throughout the respiratory cycle, and any sufficiently precise measurement of the mean cardiac electrical axis will reveal these changes in connection to breathing. One lead will suffice, however this technique is most effective when two or more readily available ECG measurements are available. The EDR can be completed even in cases of congestive heart failure, where RSA may not be present.

Indirect respiratory information extraction strategies require the simultaneous investigation of the respiratory and cardiac systems for a number of reasons. Since it has been noted that the power in the very high frequency band (0.4 Hz to half the mean heart rate expressed in Hz) shows potential utility in the diagnosis of coronary artery disease, one example of an application would be to analyze the effect of the respiratory system on heart rate variability (HRV) during stress testing. Figure 2 displays an ECG lead along with the respiratory and heart rate (HR) data (McSharry & P. ed., 2006). The respiratory signal's frequency is used to control the ECG's lead amplitude. There appears to be an imbalance between the respiratory signal and the ECG's amplitude modulation. It is also possible to determine the frequency of variation of the respiratory and HR signals.

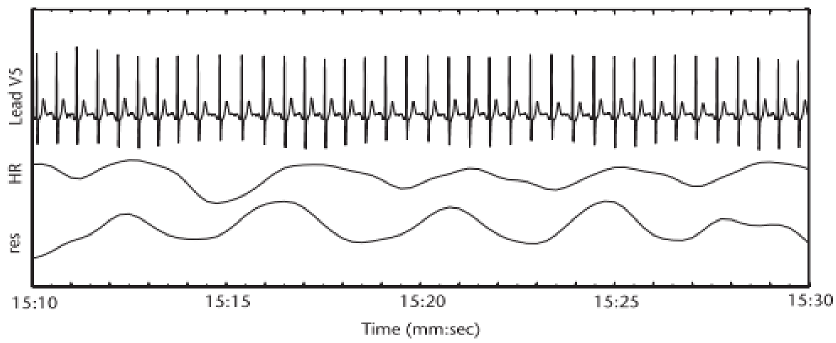

Figure 2: Lead V5 (top), HR (centre), and breathing (bottom) signals of the simultaneous ECG (McSharry & P. ed., 2006)

This study examines how physiological and technical factors affect the quality of respiratory signals in a clinical context. Both physiological and technical aspects—such as age and device design—were assessed. To improve device design and guide clinical decision-making, the quality of the extracted respiratory signals was contrasted with a reference signal (Hashoul D et al., 2019).

EXPERIMENTAL SETUP FOR DATA COLLECTION

In an experimental setup, ECG signals were acquired by standard lead configuration system and respiratory signals were simultaneously recorded by temperature sensor or pneumography technique. The band pass filter was used to remove undesired artefacts from recorded signals. The ECG is a non-invasive signal that can be recorded via the skin. By carefully examining the ECG signal, it is possible to compute several helpful metrics using the unique ECG. These measures are implemented as a sequence of intervals within a single heartbeat for cardiac safety. These time periods are essential for the accurate identification of heart conditions (Schwerdtfeger et al., 2020).

To find cardiac abnormalities, specialists manually track ECG intervals, but this is costly and time-consuming. Methods such as displacement, thermistor, resistance pneumography, and spirometer are used to measure the rate of respiration.

ECG DERIVED RESPIRATION RATE TECHNIQUES

The rate of respiration was estimated from the ECG signal using the following different EDR techniques:

A. ECG Derived Respiration Signal by Discrete Wavelet Transform (DWT) Method

The DWT decomposition method, which separates the whole signal into two components using low-pass and high-pass filters. In discrete wavelet transforms, the signal is split into two scales by the Low-pass filter (LPF) and High pass filter (HPF). The terms "approximations" and "details" are used to describe the coefficients of a low-pass filter (LPF) and a high-pass filter (HPF), respectively as shown in Figure 3 (Yi and Park, 2002).

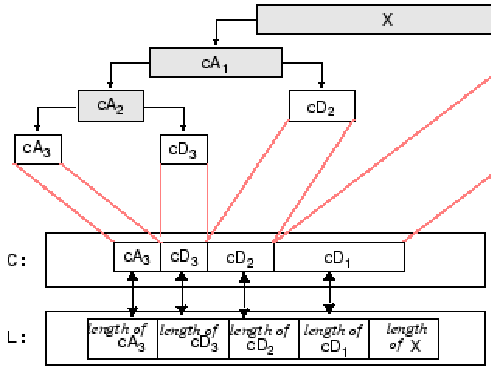

Figure 3: Wavelet Decomposition Tree (Yi and Park, 2002)

To recover respiration signals in the 0.2–0.4 Hz frequency range, the DWT approach decomposes ECG data up to the ninth level and reconstructs high-frequency components. This technique records ECG signals using bedsheet textile electrodes, offering a pleasant and dependable way to track breathing and identify sleep apnea. (Yi and Park, 2002).

B. ECG Derived Respiration Signal by RR Interval and Size of the R wave

By evaluating the magnitude of the R wave and the RR interval, the respiratory signal is derived from the ECG data. Obtaining the ECG signal and using differentiation to alter its shape constitute the first step. The slope-related data is smoothed with a band-pass filter. After identifying R peaks, the respiration rate is computed using the number of R peaks (Kim et al., 2007).

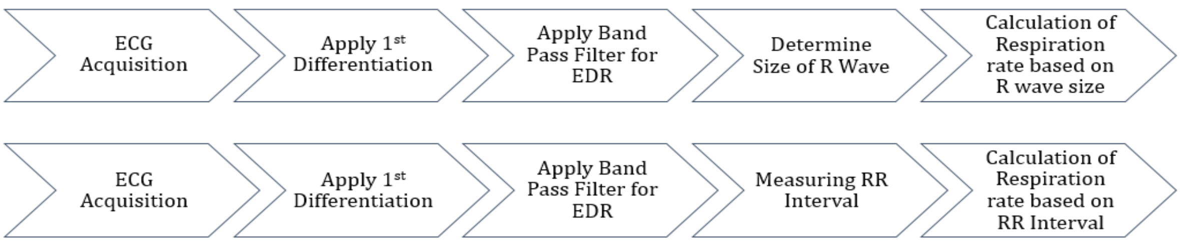

Figure 4: Flow diagram of acquiring respiration signal from an ECG based on size of R wave and RR interval

C. ECG Derived Respiration Signal by using Baseline wander noise removal

Arunachalam and Brown, (2009) described a novel method shown in Figure 5 for eliminating baseline wander noise from the ECG data in order to identify the breathing signal. Using the Fantasia database, which is accessible on Physionet.Org, this algorithm validated the estimated outcome. The estimated outcome showed that the patient records (f2y10 and f2y06) fit together well. The authors used the flow shown below to find the respiration signal (Arunachalam and Brown, 2009).

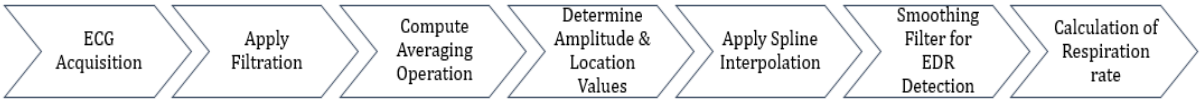

Figure 5: Flow diagram of acquiring respiration signal from an ECG by using Baseline wander noise removal

D. ECG Derived Respiration Signal by using Envelop and Interval Methods

Ruangsuwana et al. (2010) calculated EDR using methods such as interval and envelope methods. They applied two electrodes to the left ribcage and collar bone using ECG equipment. Using cubic spline interpolation, the Envelop approach connects all of the estimated R peaks. The interval approach compares actual and expected respiration rates to determine the RR interval between successive R peaks. Average correlation coefficients are higher when interval approaches are used.

E. ECG Derived Respiration Signal by Empirical Mode Decomposition Method

Campolo et al., developed Empirical Mode Decomposition (EMD) technique to estimate EDR. EMD is widely used for the analysis of biological signals due to their non-stationary and non-linear nature. EMD split the signals into many amplitude mode -frequency mode components or different oscillation modes. Additionally, EMD divide the signal into the sum of many mode functions. Algorithm's steps can be summed up as follows (Motin et al., 2019):

1. Let x (t) be the data set.
2. Locate every maximum and minimum of x(t);
3. Link the maximum and minimum points individually to generate the upper and lower envelops ($e_u(t)$, $e_l(t)$) using cubic spline interpolation;
4. Calculate $S(t) = (e_u(t) + e_l(t))/2$, the local mean;
5. Let d_1 (t) = x (t) - S (t). If d_1 (t) is a 0 average function, the iteration ends and d_1 (t) is considered as the initial mode functions, i.e., h_1 (t) = d_1 (t).
6. If not, go through steps 1-4 again with the updated data, d_1 (t), until you get to an IMF.

After obtaining the first intrinsic mode function, h_1 (t), the low frequency residual signal is subjected to a shifting operation to get the other mode functions.

Residual signal S_1 (t) defined by equation (1) (Campolo et al., 2011 & Motin et al., 2019):

$$S_1(t) = x(t) - h_1(t) \tag{1}$$

The residual signal provides a detailed description of the low frequency components. The process of shifting will continue until the final residue is homogeneous. The final noisy signal, x (t) is defined by equation (2) (Campolo et al., 2011 & Motin et al., 2019), can be represented as the sum of the low-frequency and high-frequency components, or residue signals and IMFs, respectively:

$$x(t) = \frac{1}{n}\sum_{i=1}^{n} h_i(t) + S_n(t) \tag{2}$$

F. ECG Derived Respiration Signal from 3-D Acceleration Information Using Body Sensor Network

Liu et al. (2011) generated a signal for respiration by putting an accelerometer sensor on the torso to gather data, which was subsequently filtered out using an adaptive band pass filter in conjunction with a principal component analysis (PCA) technique (Liu et al., 2011).

A device worn around the waist captured 3D acceleration impulses while the person moved and breathed, among other bodily functions. Using belly acceleration impulses from different activities, the respiration rate was calculated using power spectrum analysis. The accelerometer signal was used to calculate energy expenditure (EE). The entire quantity of energy used by the body for physiological functions, physical activity, and body composition changes is known as energy expenditure (EE). EE calculated as per below equation (3) (Liu et al., 2011):

$$\mathrm{EE} = \sum_{i=1}^{n} \Delta A\,(i) \ \text{ over 1 min} \qquad (3)$$

- Sitting and sleeping were regarded as having low EE if EE <100;
- Walking was seen as having medium EE if it was 100 ≤ EE <400;
- Running was regarded as having high EE if EE ≥400;

The study identified respiratory characteristics using Power Spectral Density (PSD) and extracted breathing vectors from belly motions using a Butterworth bandpass filter. When used on several vectors, Principal Component Analysis (PCA) proved to be more dependable and resistant to motion artifacts.

G. ECG Derived Respiration Signal by EEMD Method

The major drawback of the EMD approach is that suffering from mode mixing issue. To overcome these difficulties, respiratory rate was calculated from the ECG data using EEMD approach (Sweeney et al., 2013 & Ambekar and Prabhu, 2015).

In order to evaluate ECG signals, the Ensemble Empirical Mode Decomposition (EEMD) approach involves adding white noise to the original signal and repeating the procedure until the signal satisfies specific requirements. The one that matches the respiratory signal frequency range (0.2-0.4 Hz) is then determined by analyzing the generated intrinsic mode functions.

H. ECG Derived Respiration Signal by 4th Order Central Moment

Another literature has used RS slope analysis for determining EDR signal, which they had previously developed based on Marcus Schmidt's work (Schmidt et al., 2015).

The fourth-order central moment technique is used to estimate respiratory signals from ECG data, particularly in MRI environments, by analyzing the slope of the QRS complex and R peak amplitude.The discrete definition of a fourth-order central moment is defined by equation (4) (Schmidt et al., 2015):

$$m_4 = \frac{1}{n}\sum_{i=1}^{n}(x(i) - \bar{x})^4 \qquad (4)$$

The authors' steps for ECG-derived respiration utilizing the 4th order central moment are shown in Figure 6:

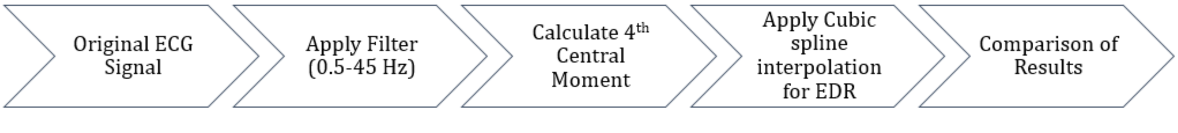

Figure 6: Flow diagram of ECG derived respiration signal by 4th order central moment

I. ECG Derived Respiration Signal with a Bank of Notch Filters

In order to compute EDR, Mirmohamadsadeghi et al. employed notch filters, concurrently extracting respiratory signals from the R peak amplitude (RPA) and respiratory sinus arrhythmia (RSA) waveforms. Patients viewed a Fantasia movie while their respiratory and ECG signals were collected. The cubic spline interpolation approach was used to interpolate the R peaks after they were extracted using the extrema detection method. Resampling the respiration signal at 4 Hz, identifying RSA, and computing RPA were all part of the experiment. A Butterworth filter was used to high-pass and a notch filter was used to remove unwanted frequencies.

J. ECG Derived Respiration Signal with HRV and PAV Method

Sarkar et al., described two ways for extracting the respiratory signal from an ECG: the HRV (Heart rate variability) approach and the PAV (Peak amplitude variation) method (Sarkar et al., 2015). Because breathing has a significant impact on the cardiac cycle, it has been noticed that the ECG may be thought of as a signal containing respiratory information, a condition known as respiratory sinus arrhythmia (RSA) (Charlton et al., 2016).

The study used the PAV technique for EDR estimate, multiresolution wavelet analysis to find the R peak, a Butterworth bandpass filter to eliminate noise from ECG signals, and linear interpolation for reconstruction. Initially, the R peaks for each of the next two cycles are identified, and RR interval is calculated by equation (5) (Sarkar et al., 2015 & Charlton et al., 2016):

$$\text{Heart rate (HR)} = \frac{60}{\text{RR Interval}} \tag{5}$$

To create the Respiratory waveform from HRV, the data of each heart rate that were thusly collected were interpolated using spline interpolation. The following formula was used to determine the Respiratory Rate (RR) using actual respiration and EDRs by equation (6) (Sarkar et al., 2015 & Charlton et al., 2016):

$$\text{Respiration rate (RR)} = \frac{t_{(n+1)} - t_{(n)}}{60} \tag{6}$$

Where,

$t_{(n+1)}$= duration till the (n+1) th R-peak occurs
t_n= amount of time when the nth R-peak occurs

K. ECG Derived Respiration Signal by Homomorphic Filtering

Sharma et al., used homomorphic filtering method to identify the respiratory signal from the ECG signal. This approach employs the Discrete Fourier Transform (DFT) and Discrete Cosine Transfrom (DCT) two transforms. After that, it compares the performance of EDR signal using Homomorphic filtering with the actual respiration signal in terms of correlation coefficient, accuracy of respiratory rate & magnitude squared coherence coefficient (Sharma et al., 2015). The technique utilizes an inverse homomorphic de-convolution operation to extract desired components after converting convolved signal components into additive form and removing undesired ones with a band pass filter using below Figure 7 (Sharma et al., 2015).

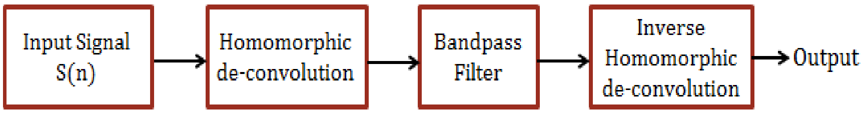

Figure 7: Block- diagram of Homomorphic Filter (Sharma et al., 2015)

The block diagram of Homomorphic de-convolution and Inverse Homomorphic de-convolution is represented by Figure 8 and 9, respectively.

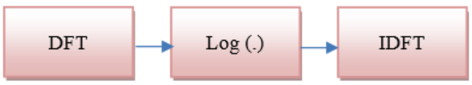

Figure 8: Block- diagram of Homomorphic de-convolution (Sharma et al., 2015)

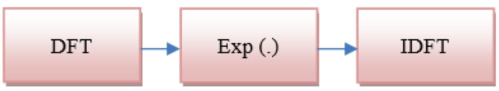

Figure 9: Block- diagram of Inverse Homomorphic de-convolution (Sharma et al., 2015)

The study used frequency domain, logarithmic function, and inverse discrete Fourier transform to successfully isolate the respiratory signal from a unipolar lead ECG.

L. ECG Derived Respiration Signal using wearable armband

Lázaro et al., 2018 introduced a wearable wristband with a pair of dry electrodes for the goal of long-term monitoring (Lázaro et al., 2018 & Lázaro et al., 2020). ECG and respiration recordings were made simultaneously on five participants, three of which were male. Respiration was recorded by Respiband which work based on Impedance plethysmography. Original respiration signals were collected in the range of 0.1 to 0.4 Hz with sampling rate of 100 Hz, whereas ECG was recorded by using wearable armband placed on left arm and recorded sampling rate of 1000 Hz (Lázaro et al., 2014).

The study generated features from the QRS complex, detected the QRS complex using wavelet analysis, and pre-processed the ECG data using a 35 Hz low pass filter. Results were compared for median, IRR, and relative error using the peak conditioned average approach and power spectral density estimation for respiratory signal extraction.

M. ECG Derived Respiration Signal using Autoencoder with a DCT Layer

Recently, Pan et al., 2023 offered a DCT Layer autoencoder-based wireless ECG-based respiratory rate (RR) estimation technique. Denoising and decorrelating data improves Mean Absolute Error (MAE) and Mean Squared Error (MSE), which in turn increases estimation precision. In the DCT domain, the DCT layer matches the input vector, improving the output of the traditional autoencoder and avoiding inaccurate results from uneven breathing. (Pan et al., 2023).

N. ECG Derived Respiration Signal using gaussian process and phase space reconstruction methods

Janbakhshi et al., 2018 suggested to use single-lead ECGs in a novel automated EDR extraction system. The system makes use of two EDR extraction methods, namely gaussian process (GP) and phase space reconstruction area (PSRArea), as well as two models: multiplicative and additive. With mean correlations of 0.706 and 0.727 with reference respiration, the system performed better than the most sophisticated single-lead EDR extraction techniques. With a single-lead ECG, this method may be helpful in identifying respiratory conditions related to sleep, such apnea (Janbakhshi and Shamsollahi, 2018).

O. ECG Derived Respiration Signal using Hermite expansion

Sharma et al., 2018 presented a new EDR technique was developed using single-lead ECG, decomposing each QRS complex using Hermite basis functions. The study hypothesizes that the quasi-periodic respiration process affects energy in the QRS complexes of the ECG signal and the spread of energy throughout the orthogonal signal. The Hermite coefficients were used to derive the respiratory signal, tracking respiratory-induced beat-to-beat fluctuations. The technique's performance was evaluated using Fantasia data, determining respiratory rate errors and correlation coefficient between EDR and measured respiration. The Hermite expansion-based EDR approach achieved a higher correlation value (0.693) and was effective for younger individuals. However, it produced minimal respiratory rate error value (1.01 bpm) for older participants compared to other EDR methods (Sharma & Sharma, 2018).

P. ECG Derived Respiration Signal in Ambulatory Monitoring using the Single-lead ECG

Varon et al., 2020 proposed methods based on QRS slopes are better than others, according to a study comparing ten algorithms for determining single-lead ECG-derived respiration (EDR). Three datasets, containing 59,482 one-minute ECG segments from 156 patients, were examined in the study. Respiratory wave morphology, respiratory rate, and cardiopulmonary information can all be reliably estimated from the ECG using straightforward techniques for respiratory information extraction, such as morphological alterations in the R-S-wave section or the slope range of the QRS complex. But there are drawbacks as well, like signal distortion, artifacts, individual variability, overlapping frequencies, and pathological situations (Varon et al., 2020).

Q. ECG Derived Respiration Signal using New Complementary Empirical Ensemble Mode Decomposition

Recently, Wan et al., 2024 proposed the new complementary ensemble empirical mode decomposition (NCEEMD) method for extracting respiration. It removes noise from the respiratory band, using modified IMF for correlation analysis. The best amplitude noise coefficient is then derived automatically. The method, compared to the Complementary Empirical Ensemble Mode Decompositio (CEEMD) technique, reduces mean square error by 3.95%, mean average error by 2.52%, and root mean square error by 2.74% in a respiration extraction comparison experiment. (Wan et al., 2024). Table 2 represents the merits and demerits of different methods used for EDR estimation.

RESULTS

Table 2 shows the advantages and disadvantages of various EDR measurement techniques.

Sr. No.	Method	Description	Overall Performance (Result Remarks)	Limitations
1.	Discrete Wavelet Transform (Yi and Park, 2002)	To determine EDR, the ECG signal is decomposed using DWT up to the ninth or tenth level, and the detail components are reconstructed.	Correlation between two series were high (above 0.9)	A lack of phase information, inadequate directionality, and shift sensitivity.
2.	RR Interval and Size of the R wave (Kim et al., 2007)	Two different methods are utilized to calculate EDR: R peak amplitude and duration of RR interval.	Accuracy obtained over 97%	Provides information only related to time domain.
3.	Baseline wander noise removal (Arunachalam and Brown, 2009)	Techniques based on continuously deducting the anticipated baseline from the ECG signal in order to eliminate baseline wander in real time.	Provides an adequate match between the real and estimated results.	Algorithm applied only two fantasia database
4.	Envelop and Interval Methods (Ruangsuwana et al., 2010)	Two algorithms were used for EDR: the envelope and interval techniques, which were compared with a breathing sensor utilizing a piezoelectric cable.	Interval method performed better than Envelop method.	Accuracy affected by mode of activity like lying down and standing
5.	Empirical Mode Decomposition (Campolo et al., 2011 and Motin et al., 2019)	EMD is used for examining non-stationary and non-linear signals.	Accuracy varies from 85 to 95% based on various modes of activity. (light activity, standing and supine)	Suffering from Orthogonal decomposition & mode-mixing problems
6.	3-D Body Sensor Network-Based Acceleration Parameter (Liu et al., 2011)	This technique used a 3D accelerator to acquire signals then a signal processing technique was used to estimate respiration rate and energy consumption.	This approach based on the frequency spectrum worked well and was resistant to motion artifact.	Not applicable for long term monitoring
7.	Ensemble Empirical Mode Decomposition (Sweeney et al., 2013 & Ambekar and Prabhu, 2015)	Mode-mixing is the major drawback of EMD approach. Adopting the EEMD algorithm helps to overcome these challenges.	Absolute error of 2.9 to 3.3%	Sensitive to noise
8.	4th order central moment (Schmidt et al., 2015)	4th central moment used to estimate respiratory signal from ECG during MRI examination	Absolute error of 2.67%	Gives reliable results inside the MR scanner only
9.	Bank of Notch Filters (Mirmohamadsadeghi and Vesin, 2015)	RSA and RPA waveform simultaneously used for EDR estimation and FIR notch filters were applied to ECG signal.	Method provided better accuracy (3.11 MAE) with smaller delay compared to previous state of art.	Very sensitive approach

10.	PAV and HRV method (Sarkar et al., 2015 and Charlton et al., 2016)	EDRs derived from HRV and PAV method and compared against Fantasia and real time database.	Mean absolute error of HRV method much less than of PAV method	Some abnormal cases, HRV and PAV method not provides good results.
11.	Homomorphic Filtering (Sharma et al., 2015)	Using the DFT and DCT transforms, this method is employed to identify the breathing parameter from the ECG data.	Accuracy of DFT transform better than DCT.	Applicable to sleep activities only
12.	Wearable Armband (Lázaro et al., 2018)	Wearable armband (consists of a pair of dry electrodes) used for estimation of respiration signal that based on IUSi, IDSi and θi methods.	R peak angle method performed better than upper and lower slope portion of R peak.	Only applicable to sleep-related activities & daily monitoring.
13.	Auto-encoder with a DCT layer (Pan et al., 2023)	Fourier analysis-based scheme was improved by using novel neural network with the DCT layer.	Autoencode with DCT layer redueses mean square error (0.1524) and mean average error (0.3025).	Enhance computational complexity due to additional operations are introduced by the DCT layer.
14.	Gaussian process and Phase space reconstruction methods (Janbakhshi and Shamsollahi, 2018)	For EDR extraction Gaussian process use additive model and Phase space reconstruction area use multiplicative model.	Mean correlations of gaussian process and phase space reconstruction area showed 0.706 and 0.727 with reference respiration.	Not suitable for other application
15.	Hermite expansion (Sharma & Sharma, 2018)	Decomposed the each QRS complex for creating Hermite function	Provide better correlation value (0.693)	Tested on only online dataset
16.	QRS slopes-based method (Varon et al., 2020)	Modifications in the R-S-wave segment's shape or the QRS complex's slope range	Important approach since the development of portable ECG-based systems requires simplicity.	Inadequate sensitivity, affected by pathological conditions, signal distortion and artifacts
17.	New complementary ensemble empirical mode decomposition (NCEEMD) (Wan et al., 2024)	Modified IMF was chosen for correlation analysis with the recorded respiratory signal	Decreases the mean square error by 3.95%, mean average error by 2.52%, and root mean square error by 2.74% as compared to the CEEMD technique.	Tested on only one dataset

DISCUSSION

A number of EDR measurement techniques are reviewed in the article, including DWT (Yi and Park, 2002), which has drawbacks such as shift sensitivity, insufficient directional details, rigid resolution, computing complexity, and edge impact. The RR Interval and Size of the R wave of the ECG signal were calculated using an algorithm based on ECG marphology (Kim et al., 2007).

ECG morphological-based methods are ineffective for EDR computations because ECG signals are non-stationary and subject to motion artifact. Data pattern loss, frequency overlap, filter design reliance, and signal distortion are among the difficulties. There are also mode-mixing problems with the EMD approach (Campolo et al., 2011 and Motin et al., 2019). To overcome this issue EEMD approach was applied to calculate EDR but the mode mixing, residual noise in IMFs, and sensitive to signal characteristics are major limitation of EEMD technique (Sweeney et al., 2013 & Ambekar and Prabhu, 2015). Wearability, data storage, allergic responses, signal quality, cost, maintenance, and device durability are some of the drawbacks of the 3-D Body Sensor Network-Based method for estimating EDR, which makes it inappropriate for long-term monitoring (Liu et al., 2011). Then, EDRs obtained via the HRV and PAV methods were then compared to the real-time database and Fantasia database (Sarkar et al., 2015). Low signal quality, trouble recording breathing depth, validation problems, and incompatibility with severe disorders are some of the drawbacks of the PAV and HRV approaches, which were only evaluated on a single dateset. Furthermore, the Homomorphic Filtering approach was developed that based on DCT and DFT method had performed well only for sleep activities (Sharma et al., 2015). After that, the combination of phase space reconstruction area (PSRArea) and gaussian process (GP) was proposed. The challenge of PSR area based EDR approach is testing the EDR's functionality in an apnea detection application. Other possible difficulties include examining the impact of various ECG leads on EDR algorithms and doing spectral analysis of EDR data for respiration rate estimate (Janbakhshi and Shamsollahi, 2018). Following that, a comparative research was proposed, which examined ten alternative EDR calculation methods in a variety of scenarios (Varon et al., 2020). After that, Hermite basis functions-based approach was employed that decomposed the each QRS complex of an ECG signal for calculating EDR. This method tested on Fantasia dataset and compared with different EDR calculating algorithms like slopes of the QRS complex, principle component analysis, R-peak amplitudes, etc and it showed greater correlation value than other methods (Sharma and Sharma, 2018). This approach worked effectively for younger people but not for older ones.

Recently, Pan et al. suggested a DCT Layer autoencoder-based wireless ECG method for RR estimation. Nevertheless, this approach has limitations, such as dependence on input properties like smoothness or periodicity, loss of local features because DCT converts input into a frequency domain, increased computational complexity from the additional operations introduced by the DCT layer, and training instability that results in longer training times or ineffective convergence. If the data does not meet these criteria, the method's performance benefits can be insignificant or nonexistent. (Pan et al., 2023). Further, a hybrid approach was introduced which was combination of two methods namely GP and PSR area (Janbakhshi and Shamsollahi, 2018). The PSR area-based EDR technique has issues with spectrum analysis, ECG lead influence, and apnea diagnosis. When evaluating EDR, the recently announced NCEEMD-based approach performs better than CEEMD in terms of mean square error, mean average error, and root mean square error (Wan et al., 2024). Limited variability, over-fitting, lack of generalization, data bias, difficulty in bench-marking, and lowered credibility are some of the drawbacks of the NCEEMD-based EDR extraction method, which was tested on a single database.

The phase space reconstruction area method is the most successful EDR estimation technique, according to the article's review of several approaches. With the highest mean correlations of 0.727 with reference respiration, our approach performs better than the majority of state-of-the-art approaches. The results facilitate the development of affordable, user-friendly ambulatory devices for monitoring cardiopulmonary parameters by permitting the application of this innovative algorithm for calculating respiratory signals using single-lead ECG.

CONCLUSION & FUTURE SCOPES

The benefits and drawbacks of several EDR estimate techniques are reviewed in this article. Certain techniques may not work in real-time situations and are only appropriate for online databases. The greatest mean correlation achieved makes the phase space reconstruction area approach preferable. In order to increase accuracy and lessen the impacts of noise, future research should concentrate on creating trustworthy algorithms employing machine learning and deep learning.

In a variety of situations, the use of multi-modal data, such as accelerometry, PPG, and ECG, can improve dependability. Personalized models and extensive clinical validation studies are required. In both home and medical settings, real-time, continuous respiration rate tracking is made possible by wearable technology and energy-efficient hardware. Several datasets will be used to evaluate the NCEEMD algorithm.

By assessing ECG-derived parameters under stress, the Hermite expansion-based EDR approach can assess sleep apnea and enhance cardiopulmonary function. In order to increase accuracy and lessen the impacts of noise, future research should concentrate on creating trustworthy algorithms employing machine learning and deep learning.

Better respiratory health monitoring and diagnostic tools are made possible by the validation and comparison of novel methodologies using standardized criteria and datasets.

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