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ANALYSIS OF BREATHING RATE ESTIMATION USING EMPIRICAL MODES

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ABSTRACT:
A crucial physiological factor that is assessed in a variety of therapeutic contexts is breathing rate (BR). But manual measurement is still extensively used. Using an electrocardiogram (ECG), photoplethysmogram (PPG), or blood pressure (BP) signal, a novel the method for measuring the BR is proposed. The framework uses Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) techniques to extract respiratory signals, utilizing data in both the time and frequency domains. These techniques were able to deliver satisfactory performance even when the signals to an Extended Kalman Filter (EKF) that contained a Signal Quality Index (SQI) were severely distorted. Prior to estimating the BR, the output signals are merged via state vector fusion. Two clinical datasets that are open to the public were used to evaluate the study.KEYWORDS :Breathing rate (BR), Electrocardiogram (ECG), photoplethysmogram (PPG), blood pressure (BP), Respiratory Rate, Respiratory Signals, Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT)

I. INTODUCTION

Breathing Rate (BR) is a crucial physiological metric that may be assessed from patients in a variety of situations, such as ERs, ICUs, and hospital wards. The sensitive indicator of patient deterioration known as BR has been demonstrated. Elevated BRs, for instance, may be present before cardiac arrest or respiratory failure. Additionally, BR can be utilised as a predictor of in-hospital mortality. Additionally, BR is used to diagnose a number of illnesses, including sepsis and pneumonia. Direct breathing monitoring sensors based on methods like spirometry, pneumography, or plethysmography are readily available. The use of these sensors is restricted to particular clinical situations, such as stressful situations and insomnia diagnosis, because they might affect breathing patterns and be intrusiveLess intrusive respiratory monitoring techniques might be more well-tolerated by patients and hence employed in a wider range of clinical situations. Numerous physiological signals that are frequently measured, such as the electrocardiogram (ECG), photoplethymogram (PPG), and blood pressure (BP) signal, can be impacted by breathing. Physiological breathing mechanisms can affect ECG, PPG, and BP data in three different ways: baseline wander (BW), amplitude modulation (AM), and frequency modulation (FM).In order to extract respiratory signals from ECG, PPG, and BP signals and then estimate BR, many techniques have been developed.The estimation of BR using ECG, PPG, and BP data has a new framework. Now we'll talk about the engineering methods used in this framework. Framework for New BR Estimations PPG, ECG and blood pressure signals Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) can be used to deconstruct a signal into a series of signals, allowing one to extract a respiratory signal here in referred to as ECG-Derived Respiration (EDR), PPG-Derived Respiration (PDR), or BP-Derived Respiration (BDR) signals.They have been widely used with ECG signals.

II. METHODOLOGY

The algorithm, which is depicted in Fig. 1, can be summed up as follows. During pre-processing, high-frequency noise and DC components are eliminated from an ECG, PPG, or BP signal. Second, utilising DWT and EMD methods, the signals are disassembled into their component elements. The PSDs of the components that correlate to respiratory signals (EDR, PDR, or BDR signals) can be used to identify them.Finally, to reduce noise from each respiratory signal, the SPI is calculated over time and paired with an EKF. The importance of the signal quality parameter becomes clearer in the noisy, low-

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quality regions of the EKF. Fourth, state vector fusion is used to generate a single respiratory signal. Finally, the BR has arrived. To begin, an ECG, PPG, or BP signal is pre-processed to remove DC components and high- frequency noise.Second, the signals are divided into components using DWT and EMD techniques. The components that correspond to respiratory signals (EDR, PDR, or BDR signals) can be recognised using their PSDs.Thirdly, to eliminate noise from each respiratory signal, the SPI is calculated over time for each respiratory signal and combined with an EKF. The signal quality parameter in the EKF is crucial, and this is especially obvious in the noisy, low-quality portions. Fourth, a single respiratory signal is generated through state vector fusion. Finally, a peak detection method is used to estimate the BR from the collected respiratory signal.

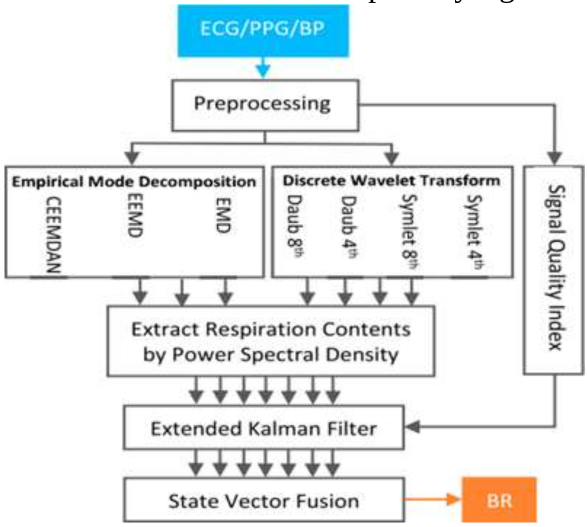


Fig 1:Block diagram of the breathing rate (BR) from an electrocardiogram , photoplethysmogram (PPG), or a blood pressure (BP) signal.

1 PRE-PROCESSING: Using a third-order Butterworth high-pass filter, the DC component of the ECG, PPG, or BP signal is eliminated. The cut-off frequency of this filter was chosen at 0.08Hz since the lowest achievable BR is 5 breaths per minute (bpm) (0.083Hz). High-frequency noise is removed using a moving average filter with a window length of 11.

EXTRACTING RESPIRATORY SIGNALS: Two well-known techniques with strong decomposition abilities were employed to extract respiratory signals: the EMD and its extended algorithm, and a DWT technique. Each method was used to generate a set of respiratory signals from the input signal (ECG, PPG, or BP). As shown in Fig.1, four respiration signals were recovered using the DWT method and three using the EMD methodology. The EMD and DWT methods are now discussed in detail.

2. EMD Methods : A flexible, totally data-driven method for evaluating non-stationary, non-linear signals is called EMD. Time series are broken down into individual components by describing the original signal as a linear combination of zero-mean amplitude and frequency modulated functions known as Intrinsic Mode Functions (IMFs), and a residual, which takes advantage of both local temporal and structural properties.Each IMF complies with the following requirements: (1) The mean of the upper and lower envelopes must be zero. (2) The number of zero-crossings and positive/negative peaks should either be equal or deviate by no more than one. When an intermittent process is present in the signal, the mode mixing problem occurs.

A single IMF having signals with vastly different scales or a signal with a similar scale present in many components is referred to as mode mixing. Individual IMFs' physiological significance is uncertain as a result of this phenomena. A Noise-Assisted Data Analysis (NADA) approach is suggested as a solution to this issue. The Ensemble Empirical Mode Decomposition (EEMD) presupposes that the white noise scale in time-frequency space is equally distribute d . The EEMD method introduces white noise into the signal to cause the components of a signal of different scales to automatically project onto correct scales of reference created by the background white noise. The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) has been demonstrated to be a

significant improvement over EEMD.CEEMDAN has an advantage over EEMD in that it achieves a low reconstruction error and solves the problem of varied number of modes for different signal plus noise realizations . EEMD and CEEMDAN techniques. The two flowcharts in Figs. 2 and 3 depict the steps for the EEMD and CEEMDAN approaches, respectively.
The PSD of each IMF is calculated, and the dominant frequency band of each IMF is identified as the 6dB bandwidth around the maximum amplitude of the PSD. The EDR, PDR, or BDR signal is then chosen as the IMF with the closest frequency band to the respiratory frequency range (6 to 33 bpm [0.10Hz, 0.55Hz]). EDR and PDR signals were derived from a 60-second frame of ECG and PPG signals (from BIDMC01, respectively). The EMD, EEMD, and CEEMDAN techniques were used to extract them. The dashed red and green lines represent the reference respiratory signal's and EDR/PDR signals' dominating frequency ranges, respectively. The major frequency bands of CEEMDAN-extracted EDR and PDR signals are theclosest to the dominant frequency band of the reference respiratory signal.

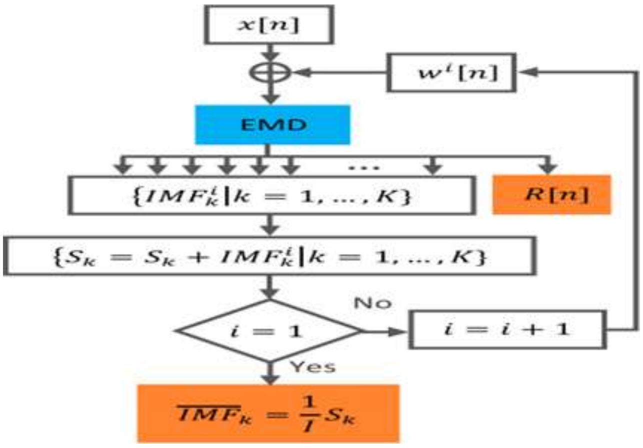


Fig2: Flowchart of EEMD based on EMD algorithm

3. Discrete Wavelet Transform:

The Wavelet Transform (WT) is a time-frequency signal analysis method that allows for simultaneous interpretation of the signal in both the time and frequency domains, allowing for the identification of local transient or intermittent components. By using the multi-resolution approach, the WT and inverse transform may be computed discretely, fast, and without signal information loss. In this investigation, respiratory components of ECG, PPG, or BP signals were extracted using the DWT with four different mother wavelet functions: 4th and 8th order Daubechies and 4th and 8th order Symlets. The PSDs of each detail signal were determined after using the DWT with these wavelet functions. The dominating frequency bands of the generated PSDs were compared to the frequency bands of the detail signal to determine the detail signal containing respiratory material.

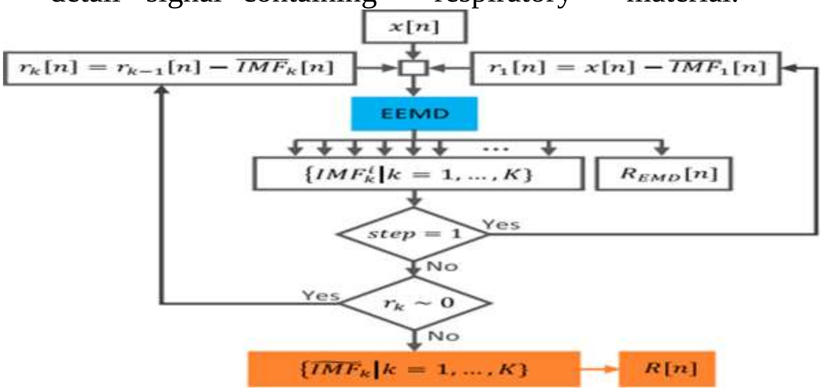


Fig3: Flowchart of CEEMDAN based on EEMD algorithm.

By using the DWT with four different wavelet functions, EDR and PDR signals were recovered from 60 second windows of ECG and PPG signals (from BIDMC01). The EDRs derived by Symlet and Daubechies 8th have the closest dominant frequency band to the reference respiratory signal's dominant frequency range. This suggests that they performed better than Symlet and Daubechies in fourth place. The performance characteristics of the wavelet functions with 4th and 8th orders. The main frequency bands of the resulting PDRs for all four mother wavelets are similar, and their performance is lower than that of EDRs.

4. SIGNAL QUALITY ASSESSMENT

By computing moments of the EEG signal power spectrum, Hjorth parameters were first suggested to extract characteristics from the spectrum of the Electroencephalographic (EEG) signal. the signal's nth order spectral moment .

$$\overline{w}_n = \int_{-\pi}^{\pi} w^n \, P(e^{jw}) \, dw$$

Where P (ejω) is the power spectrum of the signal as a function of angular frequency ω = 2πf, with f in cycles/second. The spectral moments of a signal may be calculated using a shifting overlapping window by averaging in the time domain as shown below::

$$\widetilde{\overline{w}}_i \approx \frac{2\pi}{L} \sum_{k=n-(L-1)}^{n} \left(x^{(\frac{i}{2})}(k)\right)^2$$

Where x(i/2) (k) is the i/2 derivative of x(k) and L is the window duration (L = 4s here). The SPI calculates an index for rating the quality of signals using the Hjorth descriptors. Here, we have utilised SPI as a SQI to evaluate the signal quality in the manner described below:

$$\Gamma_{SPI} = \frac{\overline{w}_2(n)^2)}{\overline{w}_0(n) w_4(n)}$$

ΓSPI is a value that ranges between 0 (total noise) and 1 (pure sinusoid), signifying low and good signal quality, respectively.

5. EXTENDED KALMAN FILTER: There are seven respiratory signals in the proposed algorithm at this point, each with a corresponding SQI parameter. Applying a KF or EKF to the respiratory signals at this stage improves their quality. Both a KF and an EKF have the ability to remove noise from a signal and then reconstruct it using a dynamic model. However, a KF can only accept a linear model, whereas an EKF can accept a nonlinear dynamic model.Since a model's accuracy can be decreased during the linearization process for use with a Kalman Filter and Extended KF may perform better than a KF. In this study, the EKF is optimised using the SQI parameter. Now that information regarding the usage of the KF and EKF. The KF is a well-known optimal state estimation method that has been proven to be the optimal filter in the Minimum Mean Square Error (MMSE) sense.

Since most systems in practise are nonlinear, the estimation accuracy must first be reduced when using the KF to approximate nonlinear dynamical models in linear form. The EKF is an extension of the standard KF that takes into account nonlinear dynamic estimate of a stochastic signal's states. To estimate the state vector in each iteration, the EKF uses a dynamical model and data generated by Kalman Gain (KG). The value of the measurement noise covariance (R) has an inverse relationship with KG. As a result, low quality measurements with greater R values have lower KG values. By reducing the value of KG for each stage, the effect of measurements on estimation is reduced, and vice versa. A multiplicative factor R is modified as follows: $R_n \rightarrow R_n (SQI_n^{-2} - 1)$

Where SQI n is the SQI of the nth sample of data which is replaced by SPI in this paper, as follows: SQIn=ΓSPI[n]

6. STATE VECTOR FUSION: 7 respiratory signals are present at this stage of the suggested method. State vector fusion is then utilised to combine the seven signals to create a single respiratory

signal. The state error covariance matrices derived from EKF are used to integrate local estimate signals in an MMSE
sense follows
:

$$\bar{x}_n = \left(\sum_{j=1}^{J} (P_n^j)^{-1}\right)^{-1} \sum_{j=1}^{J} \left[(P_n^j)^{-1} \hat{x}_n^j\right]$$

where $\bar{x}_n$ is the estimate of the overall condition at time n. J stands for the required number of signals to be fused, which in our instance is 7 (J = 7). For each of the seven respiratory signals, the $(P^j)^{-1}$ and $\bar{x}^j$, respectively, are the inverses of the state error covariance
matrices and the local state vector estimates. This implies that the state vector may be obtained more effectively with respiratory signals that work better. A global estimate of state is derived as a single fused signal for each sample of the 7 respiratory signals in order to estimate breathing rates.

7. BREATHING RATES ESTIMATION:

The detection of peaks in a fused respiratory signal. The BR was then computed by counting the number of peaks during a specific time period and expressed in beats per minute (bpm).

8. ANALYSIS :

Three metrics were used to evaluate the performance of BR algorithms.

- The Probability of Coverage CP: is the percentage of Errors that fall inside predefined boundaries,. In this case, an acceptable absolute inaccuracy in work was defined as <2bpm. The non-parametric variant of CP, denoted by The empirical cumulative distribution of the absolute was used to construct a percentage with a value of set at 2 bpm .
- MAE (Mean Absolute Error)

$$\mathbf{MAE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\mu}_{BR}(\mathbf{i}) - \mu_{ref}(\mathbf{i})| \ , \mathbf{(bpm)}$$

where $\hat{\mu}_{BR}(i)$ and $\mu_{ref}(i)$ are the estimated and reference BRs, respectively, and N is the total number of windows in the database.

- The Mean Absolute Percentage Error (MAPE):

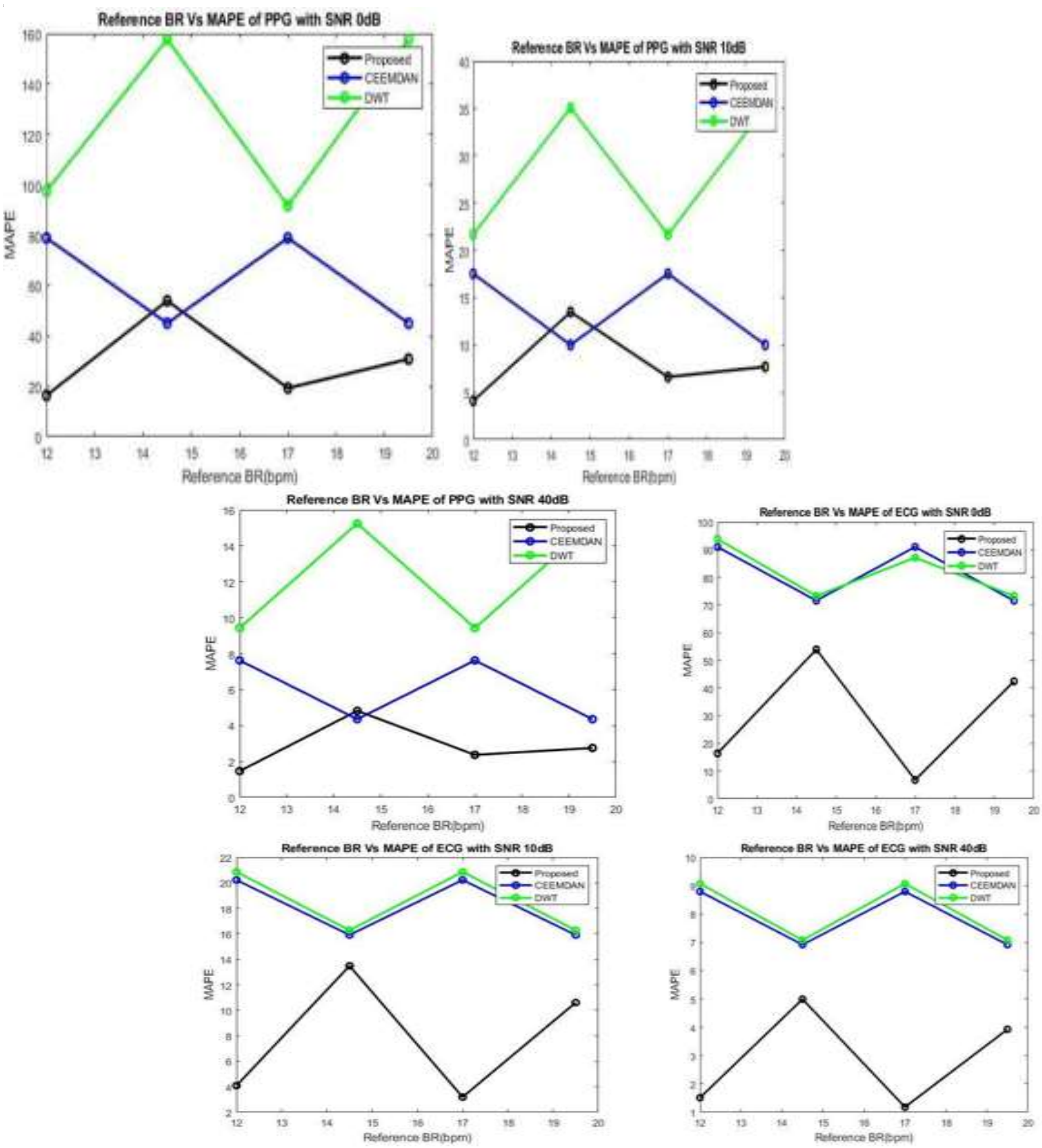
$$\mathbf{MAPE} = \frac{1}{N}\sum_{i=1}^{N} |\hat{\mu}_{BR}(\mathbf{i}) - \mu_{ref}(\mathbf{i}) / \mu_{ref}(\mathbf{i})| * \mathbf{100,(\%)}$$

The quality of each subject's ECG, PPG, or BP signals was evaluated using a metric known as Q, which is defined as the percentage ratio of the number of low quality windows Nl to the total number of windows NT of each signal:

$$Q = \frac{\boldsymbol{N1}}{\boldsymbol{NT}} * 100\%$$

Windows were considered low quality if the average in that timeframe, ┌SPI was less than 0.5. Throughout the 60-second-long analysis windows here we utilised a 50% overlap.

III .RESULTS



CONSULSION

A framework to estimate BR from ECG, PPG, or BP signals. The performance of the framework was assessed on two publicly available datasets. The work indicate that our framework shows good robustness even in presence of noise. Both EMD and DWT methods used to extract respiratory signals, obtain the advantages of each. Finally, taking into account our framework's state vector fusion approach, offer it this power to boost the impact of superior output estimate, which yields a single output with high precision.

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