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EXTRACTION OF RESPIRATORY SIGNAL FROM ECG USING SINGLE CHANNEL ECG.

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Abstract: The electrocardiogram (ECG) is widely used for diagnosis of heart diseases. Good quality ECG is utilized by physicians for interpretation and identification of physiological and pathological phenomena. In this paper we reconstruct the waveform of the respiratory signal by processing single-channel ECG. To achieve these goals, two techniques of decomposition of the ECG signal into suitable bases of functions are proposed, namely, the Empirical Mode Decomposition (EMD) and the Wavelet Analysis. The simultaneous study of both respiratory signal and ECG (Electrocardiogram) signal leads to indirect monitoring of both the signal and we can derive a respiratory signal from an ECG signal. The results show that both algorithms are able to reconstruct the Respiratory waveform, although the EMD is able to break down the original signal in an adaptive manner. The EMD leads to better result the wavelet approach.

Keywords: DWT (Discrete Wavelet Transform); EMD (Empirical Mode Decomposition).

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INTRODUCTION

The electrocardiogram (ECG) is the recording of the cardiac activity and it is extensively used for diagnosis of heart diseases. It is also an essential tool to allow monitoring patients at home, thereby advancing telemedical applications. ECG recorded from the surface of the chest is influenced by possible motion of the electrodes with respect to the heart, and by changes in the electrical impedance of the thoracic cavity. The chest expansion and contraction results in motion of chest electrodes. These physical influences of respiration result in amplitude variations in the observed ECG. In fact, the normal respiratory cycle is accompanied by changes in autonomic tone which modulate heart rate

Abnormal respiratory patterns are observed in several pathological conditions, such as congestive heart failure, central nervous system diseases, chronic lung disease, sleep apnea, metabolic disorders, etc. The precise analysis of abnormal respiratory patterns might facilitate the prediction of the patient’s prognosis and the choice of the appropriate treatment. Respiratory signals are traditionally recorded by devices such as pressure sensors attached to a strain gauge or a single band wrapped around the chest or abdominal wall, impedance sensors placed over the chest wall, and thermistors placed at the nose. However, there are two common disadvantages of using these devices: First, the complex devices involved might interfere with natural physiological breathing. Second, such devices cannot be used for certain clinical purposes, for example, ambulatory or long-term monitoring in naturalistic settings. Therefore, the development of a convenient method to record or estimate respiratory signals is important from a clinical perspective. The method used so far such as heart rate variability; It is measured by the variation in the beat-to-beat interval. "RR variability" (where R is a point corresponding to the peak of the QRS complex of the ECG wave; and RR is the interval between successive Rs), and "heart period variability". They possess disadvantage such as in real time application and it is computational costly.

In this paper two methods used for extracting an EDR (ECG derived Respiratory) signal from an ECG signal that is DWT (Discrete Wavelet Transform) and EMD (Empirical Mode Decomposition). These two methods are most relevant. The DWT can be used in order to reconstruct detail signals and to estimate the EDR (ECG Derived respiratory) signal. DWT relies on a priori choice of the wavelet basis and some experience is required in determining the level of decomposition needed to extract the RS (Respiratory signal). The main disadvantage is that it requires a prior level of decomposition for extracting a respiratory signal, so it does not suit in varying signal application.

EMD (Empirical Mode Decomposition) is intuitive and adaptive, with basic functions derived fully from the data. The computation of EMD does not require any previously known value of the signal. The key task here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly, decompose the signal into intrinsic mode functions (IMFs). .

DISCRETE WAVELET TRANSFORM

The wavelet transform provides a decomposition of the signal over a set of basis functions, obtained by dilation and translation of a mother wavelet by a scale factor S. The basis vector is obtained through a family of functions dependent on two parameters:

The dilatation (scale) coefficient.

The translation step.

The single prototype wavelet function is stretched or compressed and translated in order to recover the original signal. The Wavelet Transform provides a time frequency representation of the signal and is well suited to the analysis of non-stationary signals such as ECG. In the paper, the ECG wavelet decomposition is performed by using Single-level discrete one dimensional wavelet.

Based on the paper the EDR signal can be derived using DWT. If the ECG signal is decomposed till the Nth level of decomposition, and the detail signal of 9th decomposition is reconstructed, we get the RS (Respiratory Signal). The value of N depends upon the sampling rate. This is because the maximum frequency that can be represented is taken equal to fs/2, where fs is the sampling frequency. Because of the fact that the range frequency of RS is 0.2–0.4 Hz, it is necessary to compute the decomposition, level corresponding to this range. It performs a single-level one dimensional wavelet decomposition up to specified scale factor s=8. The mother wavelet or basis function that is used in the decomposition is Dabachies (db6 and db3), symlet (sym3 and sym6) wavelet procedure. Although DWT is limited by the size of the basic wavelet function, the downside of the uniform resolution is uniformly poor resolution.

To generate the wavelet decomposition of the signal through DWT, the fast algorithm proposed by Mallat has been used . This algorithm decomposes the signal x(t) using a set of quadrature mirror decomposition filters showing respectively low-pass and high pass properties specific to each mother wavelet. The outputs of the filter are the approximation coefficients, ylow, and the detail coefficients, yhigh, respectively

$$y_{high}(n) = \sum_{k=-\infty}^{+\infty} \mathrm{x(k)\,g(2n-k)} \quad (1)$$

$$y_{low}(n) = \sum_{k=-\infty}^{+\infty} \mathrm{x(k)\,g(2n-k)} \quad (2)$$

The resulting approximation and detail coefficients are Down-sampled by two. Then, the resulting sequences are decimated. The DWT computational cost is of the same order of the finite sequence, i.e., O (N), where N is the length of the finite Sequence in input: this represents one of the advantages of this approach along with its sparseness. The resulting approximation and detail coefficients are down-sampled by two. Then, the resulting sequences are decimated.

The DWT leads to main drawbacks of are the need of an a priori choice of the basis used for the analysis, which in turn implies the generation of an optimal wavelet through suitable techniques, and the dependence of the decomposition coefficients from the chosen basis.

EMPIRICAL MODE DECOMPOSITION

A new nonlinear technique, referred to as Empirical Mode Decomposition (EMD), has recently been pioneered by N.E. Huang et al. for adaptively representing non-stationary signals, The starting point of the Empirical Mode Decomposition (EMD) is to consider oscillations in signals at a very local level. The EMD method achieved through a linear sum of the components that approximates the original ECG signal. In this work, EMD on univariate time series has been examined. However, recently, a multivariate version of the EMD (MEMD) has been successfully proposed. The starting point of EMD is to locally estimate a signal as a sum of a local trend and a detail signal component, the local trend is a low frequency part, and the local detail accounts for high frequencies. Local trend is called residual and Local detail is Intrinsic Mode Function. The IMFs (Intrinsic Mode Function) are subject to two conditions:

In the whole data set, the number of extrema and zero crossing must be equal or differ at most by one; At any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must zeroes.

Given a signal x(t), the effective algorithm of EMD can be summarized as follows :

Identify all extrema of x(t)

Interpolate between minima (resp. maxima), ending up with some envelope emin(t) (resp. emax(t))

Compute the mean m(t) = (emin(t)+emax(t))/2

Extract the detail d(t) = x(t) − m(t)

Iterate on the residual m(t)

In practice, the above procedure has to be refined by a sifting process which amounts to first iterating steps 1 to 4 upon the detail signal d(t), until this latter can be considered as zero-mean according to some stopping criterion. Once this is achieved, the detail is referred to as an Intrinsic Mode Function (IMF), the corresponding residual is computed and

Step-5 applies. By construction, the number of extrema is decreased when going from one residual to the next, and the whole decomposition is guaranteed to be completed with a finite number of modes. A basic operation in EMD is the estimation of upper and lower “envelopes” as interpolated curves between extrema. The nature of the chosen interpolation plays an important role, and our experiments tend to confirm (in agreement with what is recommended in that cubic splines are to be preferred. Other types of interpolation (linear or polynomial) tend to increase the required number of sifting iterations and to “over-decompose” signals by spreading out their components over adjacent modes. A second point is that, since the algorithm operates in practice on discrete-time signals, some special attention has to be paid to the fact that extrema must be correctly identified, a pre-requisite which requires a fair amount of oversampling Finally, a third issue that has to be taken into account is related to boundary conditions, so as to minimize error propagations due to finite observation lengths. To this end, we obtain good results by mirrorizing the extrema close to the edges. The algorithm works iteratively by identifying the extrema of the signal and breaking it down thus ensuring that the number of modes is finite. The envelope is estimated by interpolating the extrema of the signal at each iteration.

COMPARISON OF DWT AND EMD

The Decomposition of signal into an different time scale provide by DWT and EMD methods former performs well in an adaptive and data driven way, whereas the earlier usually define a set of pre-fixed filters based on the choice of the mother wavelet. The EDR (ECG Derived Respiratory) signal has been extracted by using DWT through four different mother wavelet functions: Daubechies of 3rd order and Symlet of 3rd order. It is shown in results evident that DWT gives information on respiratory signal, but it doesn’t allow a unique reconstruction of the waveform; EMD is adaptive and can give a reconstruction of waveform.

EXPERIMENTAL RESULTS

Experiment is performed on ECG database. Results are shown below. The results are achieved using MATLB.

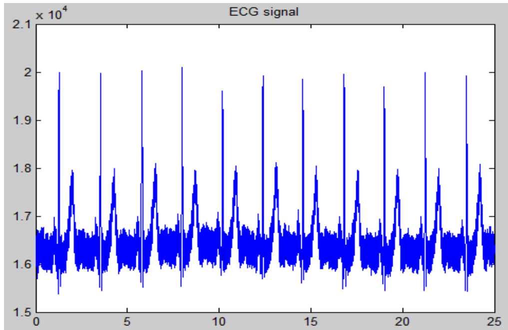

Fig. 1. ECG and Respiratory Signal

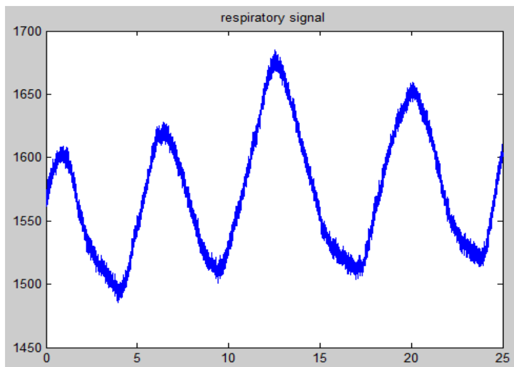

Fig. 2. Desired Respiratory Signal

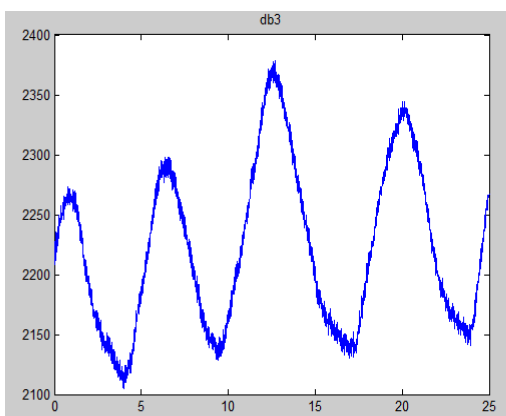

Fig. 3. DWT with mother functions db3

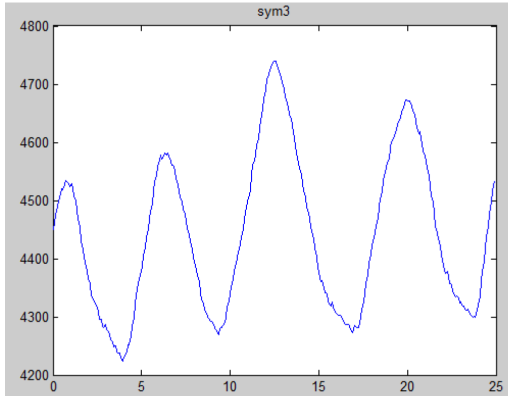

Fig. 4. DWT with mother functions sym3

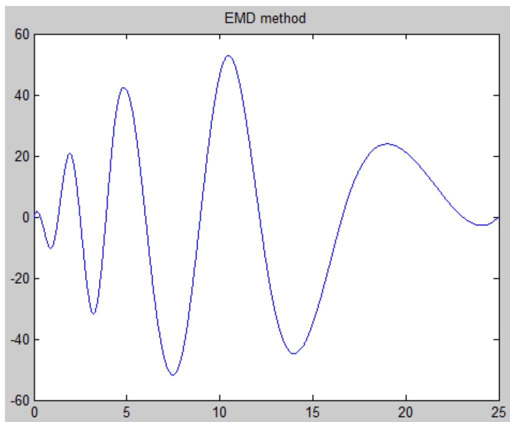

Fig. 5. EMD method for EDR

Comparison is done between Synchronous Respiratory Signal and EDR signal extracted by applying DWT and EMD method. Fig. 1 shows real ECG modulated by Synchronous Respiratory, Fig. 2 shows Synchronous respiratory signal from an ECG signal. Fig. 3 shows Extracted Respiratory Signal by DWT method with mother functions db3. Fig. 4 shows Extracted Respiratory Signal by DWT method with mother functions sym3. Fig. 5 shows EDR extracted by EMD method. The above results show both the method can reconstruct the signal in different time scale. The Difference shows here is EMD out-perform the signal decomposition adaptively and in a data driven way. Whereas looking above figure it is evident that DWT gives information on respiratory frequency, but it doesn't allow a unique reconstruction of the waveform.

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