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Extraction of Respiratory Signal from ECG using Empirical Mode Decomposition

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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, techniques of decomposition of the ECG signal into suitable bases of functions are proposed, namely, the Empirical Mode Decomposition (EMD) . 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 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.

Keywords: EMD (Empirical Mode Decomposition), Electrocardiogram, Respiratory signal, Intrinsic mode functions, Decomposition, Residual, Vector-cardiogram.

I. 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.

The Empirical Mode Decomposition (EMD) was proposed as the fundamental part of the Hilbert–Huang transform (HHT)[12]. The Hilbert Huang transform is carried out, so to speak, in 2 stages. First, using the EMD algorithm, we obtain intrinsic mode functions (IMF). Then, at the second stage, the instantaneous frequency spectrum of the initial sequence is obtained by applying the Hilbert transform to the results of the above step. The HHT allows to obtain the instantaneous frequency spectrum of nonlinear and nonstationary sequences. These sequences can consequently also be dealt with using the empirical mode decomposition. However, this project is not going to cover the plotting of the instantaneous frequency spectrum using the Hilbert transform. We will focus only on the EMD algorithm. The EMD decomposes any given data into intrinsic mode functions (IMF) that are not set analytically and are instead determined by an analyzed sequence alone. The basis functions are in this case derived adaptively directly from input data. The respiratory signal estimation is based on the identification of the intrinsic mode functions related to the respiratory activity [12].

II. EMPIRICAL MODE COMPOSITION

An Empirical Mode Decomposition (EMD) has been introduced by Huang et al. EMD 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. In EMD, the high-frequency (detail) components are referred to as Intrinsic Mode Function (IMF) and the low frequency part is called residual. The procedure is then applied again to the residual, considered as a new times series, extracting a new IMF and a new residual.

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Given a signal *x(t)*, the effective algorithm of EMD can be summarized as follows [20]:

1. identify all extrema (maxima and minima) of *x(t)*;
2. generate the upper and lower envelope (*emin(t)*, *emax(t)*) by connecting the maxima and minima points separately with cubic spline;
3. compute the local mean $r(t) = (emin(t)+emax(t))/2$;
4. extract the detail $d(t) = x(t) - r(t)$;
5. iterate on the residual *r(t)*.

At the end of the decomposition process, the EMD method expresses the signal *x(t)* as the sum of a finite number of IMFs and a final residual.

$$x(t) = \sum_{n=1}^{N} h_n(t) + r(t)$$

Where *hn(t)* are the IMFs and *rn(t)* is a final residual, which is less than an arbitrarily chosen threshold. EMD decomposes a signal x (t) into its components called intrinsic mode functions (IMFs) $h_n(t)$, n =1, 2, ...,N and the residual r(t). The algorithm as proposed by Huang is based on producing smooth envelopes defined by local maxima and minima of a sequence and subsequent subtraction of the mean of these envelopes from the initial sequence. This requires the identification of all local extrema that are further connected by cubic spline lines to produce the upper and the lower envelopes. The procedure of plotting the envelopes is shown in Figure [10]. This repeated process is called sifting. The sifting process is repeated until a certain given stoppage criterion is met. Selection of sifting stoppage criteria is one of the key points affecting the decomposition result as a whole. We will get back to the discussion of this issue a bit later. If the sifting process is successfully completed, we will get the first IMF. The next IMF can be obtained by subtracting the previously extracted IMF from the original signal and repeating the above described procedure once again.

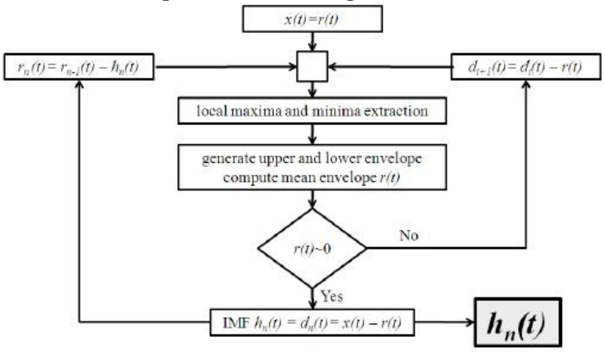

Fig.1. Empirical Mode Decomposition

This continues until all IMFs are extracted. The sifting process usually stops when the residue, for example, contains no more than two extrema.

III. RESPIRATORY SIGNAL ESTIMATION

If the ECG signal is decomposed till the N^{th} level of decomposition, and the detail signal of 9th decomposition is reconstructed, we get the RS. 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 Hz – 0.4 Hz, it is necessary to compute the decomposition, level corresponding to this range [10]. In our case the data taken is sampled at 200 Hz and the decomposition level selected is the 9th level.[12]

IV. RESULTS

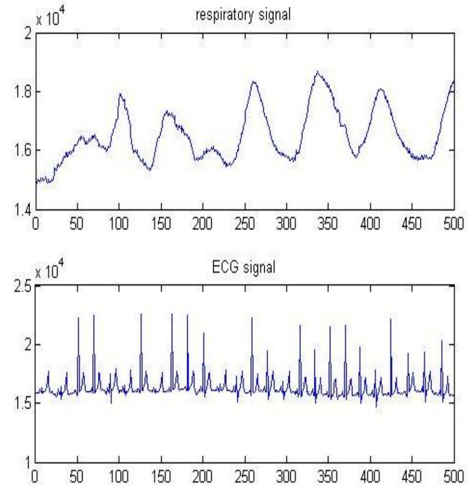

Fig.2. Modulated Single channel ECG and Respiratory Signal

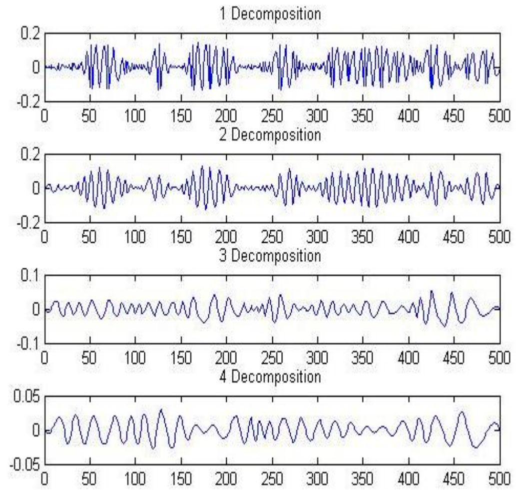

Fig.3. 1st to 4th intrinsic mode function

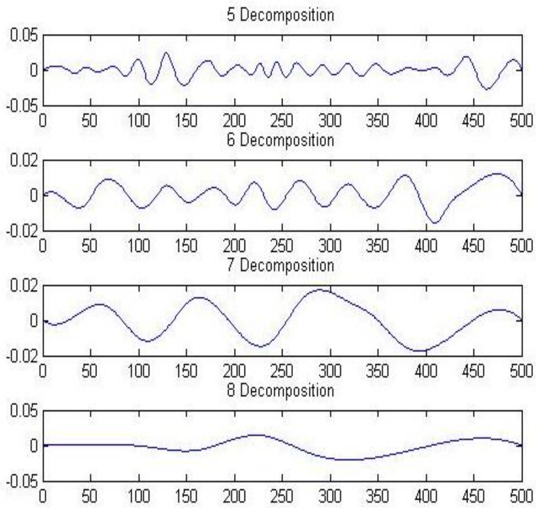

Fig.4. 5th to 8th level intrinsic mode function.

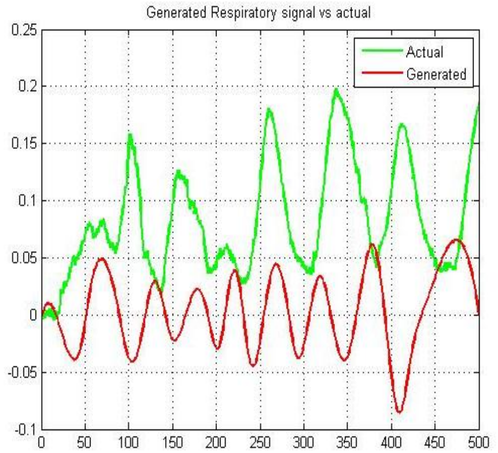

Fig. 5. Extracted respiratory signal and Original Respiratory signal.

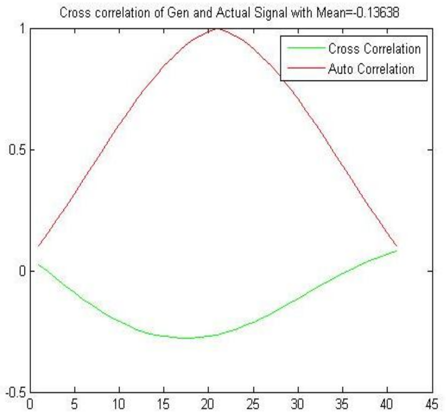

Fig. 6 Autocorrelation and Cross correlation

A. Feature Extraction Using PCA

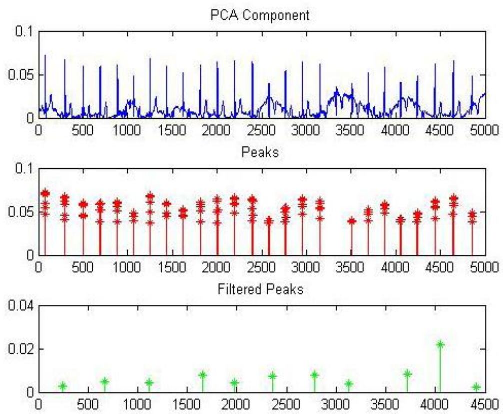

Fig. 7. Finding peaks in ECG and respiratory signal.

Principal Components Analysis (PCA) is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analysing data. The other main advantage of PCA is that once you have found these patterns in the data, and you compress the data, ie. by reducing the number of dimensions, without much loss of information. Here in Fig.7 & Fig.8 feature extraction has been carried out for calculating breathing rate of an ECG and respiratory signal.

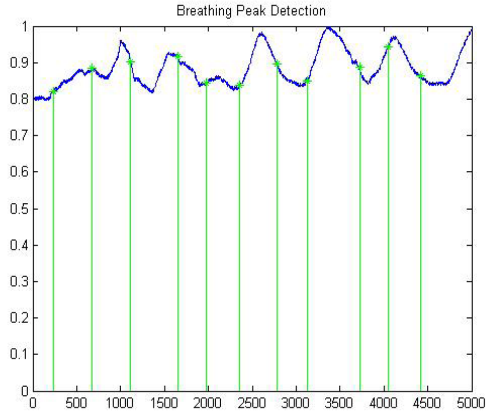

Fig. 8. Superimposing peaks on respiratory signal.

TABLE I

Generated Respiratory Rate	Actual Respiratory Rate	Accuracy
148.3	138.8	92.83

The table shows the accuracy measured based on breathing rate, which is calculated using PCA (Principle Component Analysis). It is comparison of actual and generated respiratory signal.

V. CONCLUSION

In this work empirical mode decomposition method is utilized to estimate the respiratory signal from single channel ECG signal. Wavelet decomposition is also used to extract respiratory signal from single channel ECG signal but it has been shown that empirical mode decomposition leads to better results. Some researchers, recently, are developing further improvements on EMD technique that make these new algorithms very useful and powerful instruments for indirect monitoring. This technique can also be used for the extraction of heart sound signal from auscultation process and for the analysis of heart sound signal in different critical cases.

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