A Complete Ensemble Local Mean Decomposition and Its Application in Doppler Radar Vital Signs Monitoring System

Meng Zhang[1](✉), Zhibin Yu[2], Pang Rong[2], and Gao Yuan[2]

[1] The 10th Research Institute of CETC, Chengdu 610036, China
jonmen@yean.net

[2] School of Electrical Engineering Southwest, Jiaotong University, Chengdu 611756, China

Abstract. An ensemble local mean decomposition (ELMD) method has been recently proposed to reduce mode mixing which arises in local mean decomposition (LMD). However, due to decomposition components' spectrum aliasing caused by the introduced residual noise, it is still difficult to detect the vital signs such as heart and respiration components with neighboring frequency bands by using ELMD. Therefore, a novel complete ensemble local mean decomposition (CELMD) approach, in which the obtained product function (PF) is abstracted from the residue signal for each LMD realization plus different noise, is proposed to eliminate new ones created by ELMD. To accuracy separate heartbeat and respiration components, a CELMD-based blind source separation (CELMD-BSS) method is introduced. Experimental results show that CELMD-BSS method has better separation performance for the heartbeat and the respiration component and lesser time cost due to CELMD's advantages such as smaller reconstruction error, better spectral separation of PFs and smaller time complexity.

Keywords: Local mean decomposition · Doppler radar · Vital signs detection · Signal processing · Blind source separation

1 Introduction

Using Doppler radar detecting vital life signs such as heart and respiration rate would have wide application in search and rescue operations, security and health care [1–3], because detecting vital life signs by using Doppler radar is a detecting mean of non-contact nature. According to the radar signal, we are able to remotely monitor vital life signs of a human subject. The research of detecting the vital life signs by using Doppler radar systems can be dated back to the 1970s [4], where the distinct remote monitoring advantages were demonstrated. Subsequent work in vital life signs detection area focused on improving and refining the precision of detection, where novel methods were presented to process the radar signal by using continuous wavelet transform (CWT) and short time Fourier transform (STFT) [5, 6]. However, these algorithms depend on fixed basis functions, and have limited resolution in both time and frequency. Recently, an

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automated detection method was demonstrated by using a respiration harmonic cancellation method [7]. But, a priori knowledge of the basis frequency of the respiration signal was required in this method.

Recent research on signal decomposition has resulted in fully data driven time-frequency algorithms. Such as empirical mode decomposition (EMD) [8], which can decompose adaptively a signal into a set of components. The components are termed as intrinsic mode functions (IMFs). Therefore, it is suitable for the analysis of the radar signal with nonlinear and no stationary property. The analysis method of Doppler radar signal, based on EMD, has been achieved using the measurement of heartbeat and respiration of human subject [9–11]. However, there is a loss of amplitude and frequency information due to the use of cubic splines and Hilbert transform in EMD process [12]. To reduce the loss, a local mean decomposition (LMD) was proposed recently [12], where LMD is a self-adaptive time-frequency analysis method. Using smooth local means, it can decompose adaptively a signal into a set of product functions (PFs), and each of which is a purely frequency-modulated signal. Thus, we can obtain reliable instantaneous frequency of the local oscillation signal without Hilbert transform. Therefore, the undesirable end effect and negative frequency caused by Hilbert transform can be avoided [12]. LMD's application to the electroencephalogram (EEG) was illustrated [12], and its distinct advantages were compared with the EMD in fault diagnosis [13, 14].

However, one of the main defects of the original LMD that arise with the EMD is mode mixing, which suggested that oscillations of very disparate amplitude exist in a single PF, or very similar oscillations exist in different PFs. It would lead to the individual PF components lose exact physical meaning, and it would result in the frequency aliasing of PFs too. To make up the defects above, the ensemble local mean decomposition (ELMD) algorithm was proposed [15], where an ensemble of the signal plus white Gaussian noise was decomposed by LMD. Due to the performance of the dyadic filter of LMD in white Gaussian noise [15], the mode mixing phenomenon was reduced. Although ELMD offers distinct advantages, the performance of spectral separation of PFs is reduced due to the new residual noise introduced in the reconstructed signal.

In this paper, a novel complete ensemble local mean decomposition (CELMD) approach is presented to eliminate the adverse impact of the residual noise in ELDM. A self-adjust noise coefficient is introduced in CELMD and the first PF component of an ensemble of the rest signal plus white Gaussian noise for each LMD realization is abstracted. The procedure continues with the rest PFs until the stopping criterion is reached. Doppler radar vital life signs such as heart and respiration signal are separated by using CELMD and the blind sources separation (BSS) algorithm [16, 17]. Experimental results show that the CELMD has a better spectral separation of the PFs, signal reconstruction precision, and respiration and heartbeat components are obtained by using the CELMD and BSS (CELMD-BSS) method.

2 Materials and Methods

2.1 Local Mean Decomposition

Local mean decomposition (LMD) [12] is a new data-driven method that decomposes a signal into a small set of product functions (PFs, i.e. modes) by using the smooth local mean. These PFs are the products of frequency modulation signal and time-varying signal. They contain oscillations of a signal, and the instantaneous frequency and envelope of the signal can be obtained directly by PFs. The details of LMD algorithm can be found in [12]. Formally, the original signal $x(t)$ is decomposed into k-products and a monotonic function $u_k(t)$.

$$x(t) = \sum_{p=1}^{k} \mathrm{PF}_p(t) + u_k(t) \tag{1}$$

where $\mathrm{PF}_p(t)$ denotes the *p-th* PF.

2.2 Ensemble Local Mean Decomposition

Due to signal intermittency, mode mixing might arise in the original LMD process [15]. Mode mixing would not only make the obtained PFs by LMD devoid of physical meaning, but also cause spectrum aliasing of PFs, which restricts the application of LMD method in time-frequency analysis. A similar problem also occurs in EMD [8], and it has been resolved by the added white noise in EMD process [18, 19].

Base on the noise-assisted concept, white Gaussian noise was introduced into the process of LMD and the ELMD method was proposed [15]. The added noise uniformly populates the all-time-frequency space by using the dyadic filter bank behavior of the LMD to resolve the mode mixing problem. When the signal assisted with noise is decomposed by LMD, all kinds of disparate frequency scale information in given signal which would be decomposed into corresponding frequency bands of the filter bank determined by white noise, automatically. So, the frequency aliasing phenomenon would be reduced. In addition, white Gaussian noise series are independent of each other. If the added white Gaussian noise is large enough, the ensemble mean of the noise would close to zero under ideal conditions. Thus, when the noise components being removed and the impact of white Gaussian noise is reduced in LMD. In ELMD, the given signal x(t) is decomposed multiple times with the addition of different white noise w(t), and the obtained ensemble means of multiple times decomposition is known as the final results.

2.3 Complete Ensemble Local Mean Decomposition

Due to the LMD's dyadic filter bank behavior in the presence of white Gaussian noise, the mode mixing phenomena is reduced in ELMD algorithm [15]. Figure 1 shows the dyadic filter bank behavior of LMD using white Gaussian noise. From Fig. 1, it can be seen that the value of PSD1 is quite low in the normalized frequency ranges 0–0.2. In this range, PSD1 overlaps rarely with other PSDi (i = 2, 3, 4, 5). However, PSDi (i = 2, 3, 4, 5) is partial overlap with PSD(i + 1), and the overlapping range of the corresponding

PFs' frequency bands increases with an increase in i step by step. The results indicates that the different frequency content of a given signal might still be decomposed into the same frequency bands by ELMD, which suggested that the mode mixing phenomena is not reduced significantly in ELMD process which only relies on the ensemble means of corresponding PFs. From ELMD, the extra added noise may lead to new problems such as the reconstruction error and the different number of PFs for different realizations of the signal plus noise.

Therefore, considering the spectral separation characteristics of the first component (PF1), a novel method that only concerns PF1 for each ELMD realization is here proposed.

Suppose $\overline{PF}_k$ indicates the decomposed components, after $\overline{PF}_1$ is obtained by ELMD, the first unique residue $u_1(t)$ can be calculated as

$$u_1(t) = x(t) - \overline{PF}_1 \tag{2}$$

where $x(t)$ is the original signal. Then, calculate the first PF (mode) over an ensemble of $u_1(t)$ plus different white Gaussian noise by applying LMD multiple times. The first PF is obtained by averaging and it is regarded as the second product function $\overline{PF}_2$ of $x(t)$. The next residue is defined as

$$\begin{aligned} u_2(t) &= u_1(t) - \overline{PF}_2 \\ &= x(t) - (\overline{PF}_1 + \overline{PF}_2) \end{aligned} \tag{3}$$

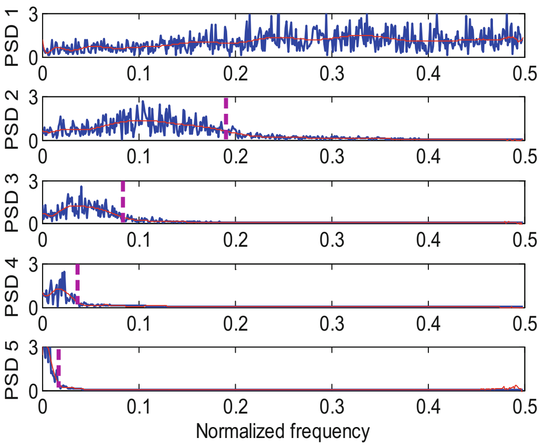

Fig. 1. The dyadic filter bank behavior of LMD using white noise. The data length is 512 data points. The vertical axis is the average PSD of each component PF for 100 times LMD with different white Gaussian noise.

Repeat the above procedure with the rest of PFs until the stopping criterion is reached. We define the operator $\text{LMD}_j[\cdot]$ and $\text{std}[\cdot]$ indicate respectively the *j-th* PF obtained by LMD and the standard deviation for the analyzed signal. Let $w(t)$ corresponds to a white

Gaussian noise with N (0, 1) and ε_0 denotes the magnitude of the added noise. The proposed approach is summarized in the following Algorithm 1.

According to Algorithm 1, the final residue can be calculated as

Algorithm 1: Complete Ensemble Local Mean Decomposition (CELMD)

1. Generate $y(t) = x(t) + \varepsilon_0 w(t)$ based on the original signal $x(t)$ and white Gaussian noise $w(t)$ with a finite amplitude ε_0.
2. Decompose $y(t)$ into PFs using LMD.
3. Repeat the first two steps again and again, until the ensemble size M is reached, but with different noise series for each LMD realization.
4. Take the ensemble mean $\overline{PF_1}(t) = \frac{1}{M}\sum_{i=1}^{M} PF_1^i(t)$ of $PF_1^i(t)$ as the final decomposition result of the 1-*th* PF of $x(t)$, where $i = 1, \cdots, M$ denotes the labels of the ith LMD realization.
5. Calculate the residue $u_k(t) = u_{(k-1)}(t) - \overline{PF}_k(t)$, ($k = 1, \cdots, K-1$), where K indicates the number of PF components and $u_0(t) = x(t)$.
6. Replacing $y(t)$ by $U_k^i(t) = u_k(t) + \varepsilon_0 \cdot \mathrm{std}[u_k(t)] \cdot \mathrm{LMD}_k[w^i(t)]$, repeat the second and the third steps, and take the ensemble means
$$\overline{PF}_{(k+1)}(t) = \frac{1}{M}\sum_{i=1}^{M} \mathrm{LMD}_1[U_k^i(t)] \quad (4)$$
as the final decomposition results of the $(k+1)$th component of $x(t)$.
7. Go back to the 5 step to repeat the same procedure for next k, until a stoppage criterion is reached.

$$u(t) = x(t) - \sum_{k=1}^{K} \overline{PF}_k \tag{5}$$

according to the Eq. (5), the given signal $x(t)$ can be expressed by the Eq. (6).

$$x(t) = \sum_{k=1}^{K} \overline{PF}_k(t) + u(t) \tag{6}$$

the Eq. (6) indicates that the proposed approach can provide an exact reconstruction of the original signal. The finite amplitude ε_0 need be selected by the given signal. Concerning the amplitude ε_0 of the added noise, high frequency signals are added to noise of small amplitude value [19] and vice versa. The obtained PFs set consists of $\overline{PF_1}^i(t)(i = 0, 1, \cdots, K)$ which are obtained as

$$\overline{PF}_1^i(t) = \frac{1}{M}\sum_{m=1}^{M} \mathrm{LMD}_1[U_{i-1}^m(t)]$$

The frequency characteristics and the corresponding filter bank property of CELMD are illustrated by applying a single delta signal $\delta(t)$ which was used to analyze the filter bank property of complete ensemble empirical mode decomposition (CEEMD) [18].

3 Application to Doppler Radar Data

In Doppler radar vital life signs monitoring system, the received radar signal contains a frequency shift proportional to the speed of the monitored-target due to Doppler Effect. If the monitored-target is human thorax, the received Doppler echo radar signal includes possible the heartbeat and respiration information due to the chest motion resulted in heartbeat and respiration. In order to separate heartbeat and respiration signals from Doppler echo signal, a time-frequency analysis method which has good frequency resolution is required. According to the LMD theory and the analysis in Sect. 2, the proposed CELMD algorithm has a good time-frequency resolution and robust property, and it suitable for nonlinear and non-stationary Doppler radar data analysis. Accordingly, CELMD-based blind source separation (CELMD-BSS) method consists of three parts: decomposing the radar signal with CELMD, reducing noise and estimating the number of components with PCA, and estimating heart and respiration components with a joint diagonalization method.

The Doppler radar vital life signs data used in this study was obtained from a low cost Doppler radar. Signal acquisition was carried out using a USB audio interface with a camera frequency of fc = 10.587 GHz. The radar to human chest distance was 30cm, the data sampling rate was 44.1 kHz. Figure 2(a) shows the Doppler radar signal and its' FFT spectrum. In the FFT spectrum, the received radar signal includes apparently two components respiration (0.5 Hz) and heartbeat (1.4 Hz). ECG signals corresponding to Fig. 2 (a) is plotted in Fig. 2 (b).

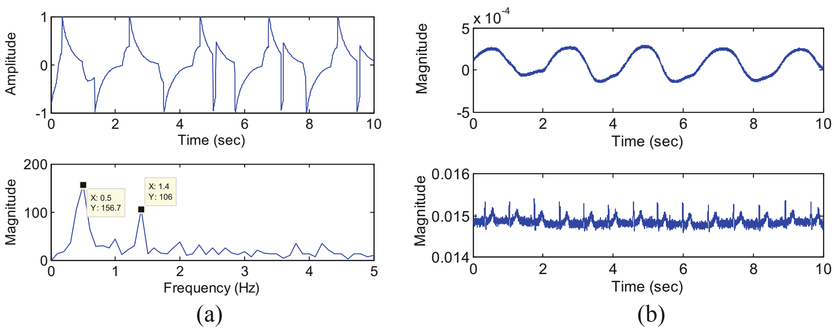

Fig. 2. The radar signal and ECG reference. (a) the received radar (top) and its FFT spectrum (bottom), (b) ECG reference(top: respiration, bottom: heart)

In order to reconstruct respiration and heartbeat signals, the CELMD method is applied. For comparison, replacing CELMD with ELMD and CEEMD, signal separation results are shown in Fig. 3. It can be clear seen that the reconstruction result of CELMD is better than that of ELMD, and got pretty much the exact same results with CEEMD. However, in ELMD, the heartbeat component cannot be reconstructed due to spectral separation performance decreased in ELMD.

In Fig. 4, it shows separation results of heart and respiration by using two decomposition methods (CELMD, and CEEMD) and BSS. As the reconstruction result of the heart component is not obtained, the separation result of ELMD is not plotted in Fig. 4. Compared with the results shown in Fig. 3, the estimation performance of heart and respiration components are improved by using BSS. In Fig. 4, separation results obtained by CELMD-BSS and CEEMD-BSS are approach to the ECG references, and that the FFT spectrums shown in Fig. 5 corresponding to the signals obtained by using CELMD-BSS and CEEMD-BSS in Fig. 4 are also close to the spectrum of the ECG reference, which suggested that a similar separation result can be obtained by using the two methods.

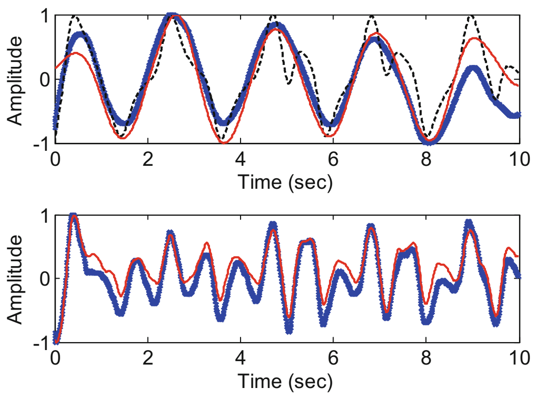

Fig. 3. Reconstruction results of heart and respiration by using the energy frequency filter where three decomposition methods CELMD (blue line), ELMD (dotted black line) and CEEMD (red line) are used.

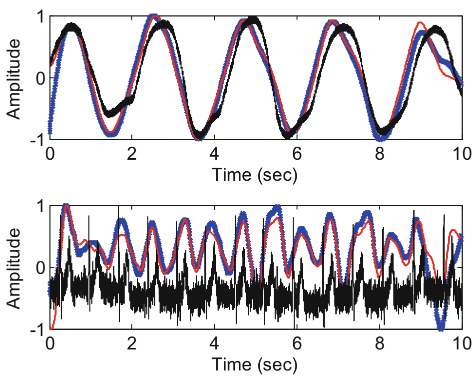

Fig. 4. Separation results of heart and respiration by using two decomposition methods (CELMD (blue line) and CEEMD (red line)) and BSS (ECG reference: black line).

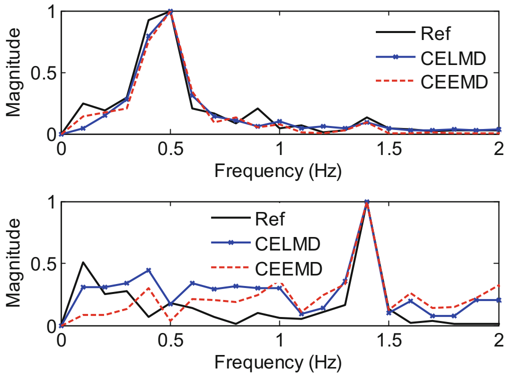

Fig. 5. Spectrums of heart and respiration corresponding to signals of the ones in Fig. 4.

4 Conclusions

In this paper, we proposed a novel CELMD-BSS approach to extract the heart and respiration from the Doppler radar vital sign monitoring system. The new reside noise component introduced in ELMD is reduced by using the presented CELMD method. Compared ELMD, CELMD has better spectral separation of PFs and smaller reconstruction error; compared CEEMD, CELMD has lesser time cost. Therefore, the presented CELMD is suited to processing nonlinear and non-stationary data. Based on CELMD, we introduced the BSS method to separate the heart and respiration components. The experimental results proved that heart and respiration components can be accuracy separated by the proposed CELMD-BSS. The CELMD-BSS method here proposed is suitable for underdetermined and over-determined blind source separation of the vital signs signal without prior know.

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