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Parallel Implementation of Empirical Mode Decomposition for Nearly Bandlimited Signals via Polyphase Representation

Qiuliang Ye · Bingo Wing-Kuen Ling · Daniel P.K. Lun · Weichao Kuang

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Abstract Nearly bandlimited signals play an important role in the biomedical signal processing community. The common method to analyze these signals is via the empirical mode decomposition approach which decomposes the nonstationary signals into the sums of the intrinsic mode functions. However, this method is computational demanding. A natural idea to reduce the computational cost is via the block processing. However, the severe boundary effect would happen due to the discontinuities between two consecutive blocks. In order to solve this problem, this paper proposes to realize the parallel implementation via polyphase representation. That is, the empirical mode decomposition is implemented on each polyphase components of the original signal. Then each sub-signals are combined after upsampling. The simulation results show that our proposed method achieves the approximate intrinsic mode functions both qualitatively and quantitatively very close to the true intrinsic mode functions. Besides, compared with the conventional block processing method which significantly suffered from the boundary effect problem, our proposed method does not have this issue.

Keywords Empirical mode decomposition · Polyphase representation · Parallel implementation · Bandlimited signals

Qiuliang Ye · Bingo Wing-Kuen Ling(✉) · Weichao Kuang
School of Information Engineering,
Guangdong University of Technology,
Guangzhou, People's Republic of China
E-mail: yongquanling@gdut.edu.cn

Qiuliang Ye · Daniel P.K. Lun
Department of Electronic and Information Engineering,
The Hong Kong Polytechnic University,
Hong Kong, China

1 Introduction

Many human body signals such as PPG, ECG and EEG signals are localized in very narrow frequency bands. They are nearly bandlimited. Besides, they are nonstationary. In order to analyze these signals, an adaptive approach called the empirical mode decomposition approach is employed [1, 2, 3, 4]. As a powerful time-frequency analysis tool, the empirical mode decomposition have been applied in the estimation of instantaneous frequency, pre-processing and feature preselection applications [5, 6, 7]. Besides, some improvements of empirical mode decomposition with masking signals or Gaussian white noise can be found in [8, 9].However, the empirical mode decomposition is an iterative process which requires to find the extrema of the signal, perform the interpolation among the extrema and subtract the original signal from the interpolated signal in each iteration. Hence, the required computational power for performing the empirical mode decomposition is large. Therefore, there is a great demand to have a parallel implementation of the empirical mode decomposition for the nearly bandlimited signals.

The common method for the parallel processing is via the block processing approach [10, 11, 12]. That is, the signal is divided into a finite number of blocks of sub-signals with each block of the sub-signal is localized in a particular time support.However, in general, the numbers of the intrinsic mode functions of different blocks of the sub-signals are different. Hence, it is difficult to obtain the intrinsic mode functions of the original signal based on the intrinsic mode functions of the blocks of the sub-signals. Besides, the final value of the intrinsic mode function of a previous block of the sub-signal may not be equal to the initial value of the intrinsic mode function of the next block of the sub-signal. This leads to the occurrence of the discontinuities at the boundaries of two consecutive blocks of the sub-signals. This is known as the boundary effect.

To address the above problem, this paper proposes to break down the signal into the polyphase components via the downsampling approach. Then, each polyphase component is represented as the sum of the intrinsic mode functions. Next, the intrinsic mode functions of the polyphase components are upsampled. Finally, the upsampled intrinsic mode functions are combined to obtain the approximated intrinsic mode functions of the original signal. Since the nearly bandlimited signals are oversampled, the values of the original signal within a local neighborhood are almost the same. Hence, different polyphase components are very similar. This implies that the numbers of the intrinsic mode functions of different polyphase components are almost the same. Therefore, the intrinsic mode functions of the original signal can be approximated by the intrinsic mode functions of the polyphase components. However, there are still differences among different polyphase components even though these differences are very small. These differences may result to the occurrences of the oscillations in the approximated intrinsic mode functions. To suppress these oscillations, a simple lowpass filtering approach is applied. The computer numerical simulation results show that the errors between the true intrinsic mode functions and the approximated intrinsic mode functions of the original signal are very low.

The outline of this paper is as follows. Section 2 presents the proposed parallel implementation of the empirical mode decomposition. The computer numerical simulations are presented in Section 3. Finally, a conclusion is drawn in Section 4.

2 Proposed Parallel Implementation of Empirical Mode Decomposition

A signal $x[n]$ is called nearly bandlimited with the oversampling factor $L \in Q$ if nearly all energy of the signal is localized within the frequency band $[-\pi/L, \pi/L]$. The polyphase representation of $x[n]$ with M polyphase components is defined as [13, 14]:

$$X(z) = \sum_{i=0}^{M-1} z^{-i} X_i(z^M), \tag{1}$$

where $X(z)$ is the z-transform of $x[n]$ and $X_i(z^M)$ is the ith polyphase component of $X(z)$. It is worth noting that if $L > M$, then $X_i(z^M)$ is also nearly bandlimited with the oversampling ratio M. Hence, if $X_i(z^M)$ is downsampled by M, then the aliasing effect is small. As a result, different polyphase components are very similar to each others. Therefore, the numbers of the intrinsic mode functions of different polyphase components are almost the same.

Now, the empirical mode decomposition is applied to $x[Mn+i]$ and we have

$$x[Mn+i] = \sum_{j=1}^{N_i-1} c_{i,j}[n] + r_i[n] \ \forall i \in \{0, \cdots, M-1\}, \tag{2}$$

where $c_{i,j}[n]$ and $r_i[n]$ is the jth intrinsic mode function and the residue of $x[Mn+i]$, respectively.

It is worth noting that the sifting process of the traditional empirical mode decomposition acts as the iterative highpass filtering [15, 3]. That is, finding the mean envelope of a signal in each iteration and performing the adaptive interpolation act as the lowpass filtering. Therefore, subtracting the mean envelope in each iteration is equivalent to perform the highpass filtering. Fig. 1 plots the magnitude responses of the first four intrinsic mode functions of a PPG signal. Although these frequency bands are overlapped each others, it can be seen from Fig. 1 that the widths and the peak frequencies of these bands decrease as the sifting process proceeds.

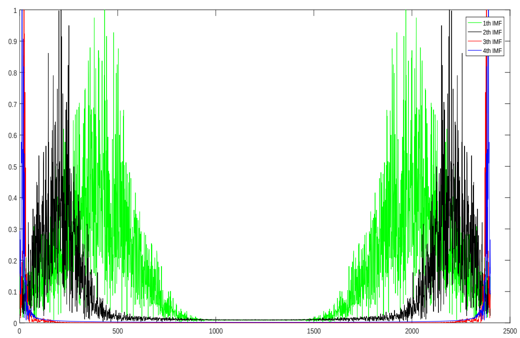

Fig. 1 The magnitude responses of the first four intrinsic mode functions of a PPG signal.

As explained in the above, $x[Mn+i]$ is also nearly bandlimited. Hence, the aliasing effect is small and the polyphase components preserve the shape of the original signal. Fig. 2 shows the magnitude responses of the first intrinsic mode function of the first four polyphase components of the PPG signal. It can be seen from Fig. 2 that the amplitudes and the frequency bands of these polyphase components are very similar to each others.

Suppose that $c_j[n]$ and $r[n]$ is the jth intrinsic mode function and the residue of $x[n]$, respectively. That is

$$x[n] = \sum_{j=1}^{N-1} c_j[n] + r[n]. \tag{3}$$

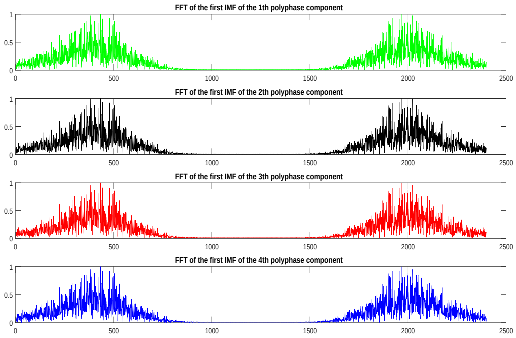

Fig. 2 The magnitude responses of the first intrinsic mode function of the first four polyphase components of the PPG signal.

Then, we have

$$\sum_{j=1}^{N-1} C_j(z) + R(z) = \sum_{i=0}^{M-1} z^{-i} (\sum_{j=1}^{N_i-1} C_{i,j}(z^M) + R_i(z^M)). \tag{4}$$

Here, $C_j(z)$, $R(z)$, $C_{i,j}(z)$ and $R_i(z)$ are the z-transforms of $c_j[n]$, $r[n]$, $c_{i,j}[n]$ and $r_i[n]$, respectively.

If $N_i = N \; \forall i$, then we have

$$\sum_{j=1}^{N-1} C_j(z) + R(z) = \sum_{j=1}^{N-1} (\sum_{i=0}^{M-1} z^{-i} C_{i,j}(z^M)) + \sum_{i=0}^{M-1} z^{-i} R_i(z^M). \tag{5}$$

Hence, we have

$$C_j(z) \approx \sum_{i=0}^{M-1} z^{-i} C_{i,j}(z^M) \; \forall j \in \{1, \cdots, N-1\} \tag{6}$$

and

$$R(z) \approx \sum_{i=0}^{M-1} z^{-i} R_i(z^M). \tag{7}$$

Now, consider the case where $\exists i$ such that $N_i < N$. For these values of i, define $c_{i,j}[n] = 0$ for $N_i \le j \le N-1$ and reset $N_i = N$. Then, (6) and (7) are applied. On the other hand, consider the case where $\exists i$ such that $N_i > N$. Define an index set S that contains these values of i. Then, we have

$$\sum_{j=1}^{N-1} C_j(z) + R(z) = \sum_{j=1}^{N-1} (\sum_{i=0}^{M-1} z^{-i} C_{i,j}(z^M)) + \sum_{i=0}^{M-1} z^{-i} R_i(z^M) + \sum_{i \in S} z^{-i} \sum_{j=N}^{N_i-1} C_{i,j}(z^M). \tag{8}$$

Now, we have

$$C_j(z) \approx \sum_{i=0}^{M-1} z^{-i} C_{i,j}(z^M) \; \forall j \in \{1, \cdots, N-1\} \tag{9}$$

and

$$R(z) \approx \sum_{i=0}^{M-1} z^{-i} R_i(z^M) + \sum_{i \in S} z^{-i} \sum_{j=N}^{N_i-1} C_{i,j}(z^M). \tag{10}$$

From the above, it can be seen that the intrinsic mode functions of the original signal can be approximated by the intrinsic mode functions of its polyphase components. As the lengths of the polyphase components are shorter than the length of the original signal, the required computational powers for computing the approximated intrinsic mode functions are much reduced.

However, there are time delays among different polyphase components. In fact, the approximated intrinsic mode functions are the sums of the delayed version of the upsampled intrinsic mode functions of the polyphase components. Hence, this may lead to the occurrences of the oscillations in the approximated intrinsic mode functions. To suppress the oscillations in the approximated intrinsic mode functions, a simple lowpass filtering is applied to smoothen these oscillations.

3 Computer Numerical Simulation Results

To evaluate the performance of our proposed method, the ratio of the error energy between the ith true intrinsic mode function and the ith approximated intrinsic mode function to the energy of the ith intrinsic mode function of the original signal is employed as the metric. That is

$$Err_j = \frac{\sum_{n=1}^{N} |c_j[n] - \bar{c}_j[n]|^2}{\sum_{n=1}^{N} |c_j[n]|^2}, \tag{11}$$

where $\bar{c}_j[n] = \sum_{i=0}^{M-1} c_{i,j}[n+i]$ is the jth approximated intrinsic mode function of $x[n]$.

To demonstrate the effectiveness of our proposed method, all simulations are conducted using MATLAB run on a workstation with Windows OS and Intel Core i7 CPU.

3.1 Example: Ideal sinusoidal signal

Consider a toy example of an oversampling sinusoidal signal with four tones as follows:

$$x[n] = 0.15 \sin(2\pi * 0.035n) + 0.35 \sin(2\pi * 0.025n) + 0.25 \sin(2\pi * 0.015n) + 0.25 \sin(2\pi * 0.005n).$$

(12)

It is worth noting that different tones have different amplitudes and frequencies. These amplitudes and frequencies are chosen in such a way that the mode fixing phenomenon does not occur [16]. Besides, the total number of the polyphase components M is chosen as 5 and the length of the original signal is chosen as 20000.

Here, the conventional block processing method is employed to compare with our proposed method. For the block processing method, the original signal is divided into 5 non-overlapping blocks with each block having the length 4000. After performing the empirical mode decomposition on each block of the signal, those 2nd intrinsic mode functions of these 5 blocks of the signal are combined to form a 20000 point approximated 2nd intrinsic mode function. It is worth noting that the envelop of the signal in each block is very different from that of the original signal. Therefore, only the intrinsic mode functions with their indices smaller than or equal to the total number of the intrinsic mode functions of the original signal are considered in the block processing method. Fig. 3 shows the 2nd true intrinsic mode function as well as that obtained by our proposed method and the block processing method. It can be seen that our proposed method can achieve the approximated intrinsic mode function very close to the true intrinsic mode function without suffering from the boundary effect. On the other hand, the approximated intrinsic mode function obtained by the block processing method is severely suffered from the boundary effect. That is, there are very large discontinuities along the boundaries of the blocks. This implies that our proposed method qualitatively outperforms the block processing method for this demonstrated signal. In this example, the total number of the intrinsic mode functions of the original signal is 4. Hence, the errors of these four intrinsic mode functions are evaluated. Table 1 shows these errors obtained by both our proposed method and the block processing method. It can be seen that the errors obtained by our proposed method are much smaller than that obtained by the block processing method. Hence, our proposed method quantitatively outperforms the block processing method. Besides, Table 2 lists the required computational time for performing the empirical mode decomposition directly on the original signal as well as that via the block processing method and our proposed method. Compared with the required computational time for performing the empirical mode decomposition directly on the original signal, the required computational time of our proposed method is much smaller. Though our proposed method requires a more computational time than the block processing method, our proposed method both qualitatively and quantitatively outperforms the block procesing method.

Table 1 Errors of the approximated intrinsic mode functions (IMF) obtained by both our proposed method and the block processing method.

Methods	Proposed method	Block processing method
1st IMF	2.7x10^{-5}	1.04x10^{-2}
2nd IMF	7.48x10^{-5}	3.46x10^{-2}
3rd IMF	11.1x10^{-5}	29.35x10^{-2}
4th IMF	11.8x10^{-5}	60.01x10^{-2}

Table 2 Required computational time (in seconds) for performing the empirical mode decomposition (EMD) directly on the original signal as well as that via the block processing method and our proposed method.

Direct EMD	Block processing	Proposed method
0.042762	0.015510	0.024935

Fig. 4 plots the 4th intrinsic mode functions of all the polyphase components of the original signal. It can be seen that there are differences among different polyphase components even though these differences are very small. As the approximated intrinsic mode functions are the sums of the delayed version of the upsampled intrinsic mode functions of the polyphase components, this may result to the occurrences of the oscillations in the approximated intrinsic mode functions.

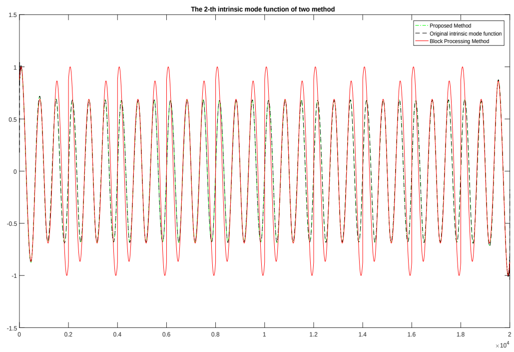

Fig. 3 The 2nd approximated intrinsic mode functions obtained by both our proposed method and the block processing method.

3.2 Example: PPG signal

Now, consider a second example downloaded from the PhysioBank ATM database which is a practical wrist PPG signal acquired during an exercise [17]. The signal

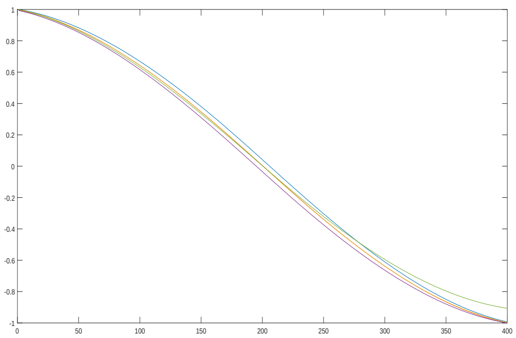

Fig. 4 The 4th intrinsic mode functions of all the polyphase components of the original signal.

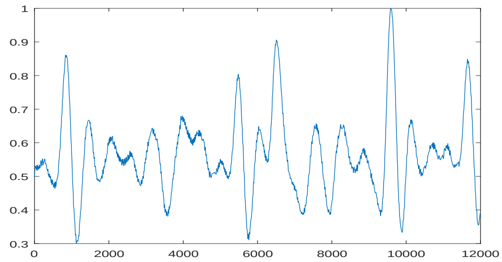

Fig. 5 Original wrist PPG signal.

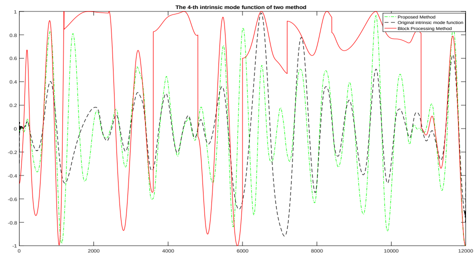

Fig. 6 *The 4th approximated intrinsic mode functions obtained by both our proposed method and the block processing method.*

is shown in Fig. 5. Fig. 6 shows the 4th true intrinsic mode function of the original signal as well as the 4th approximated intrinsic mode functions obtained by both our proposed method and the block processing method. It can be seen that the 4th approximated intrinsic mode function obtained by the block processing method is completely different from that of the 4th true intrinsic mode function of the original signal. On the other hand, the 4th approximated intrinsic mode function obtained by our proposed method preserves the shape of the 4th true intrinsic mode function of the original signal. This implies that our proposed method qualitatively outperforms the block processing method for this practical nearly bandlimited signal. In this example, the total number of the intrinsic mode functions is 5. Table 3 lists that the errors of these intrinsic mode functions obtained by both our proposed method and the block processing method. It can be seen that the errors obtained by our proposed method are lower than those by the block processing method. Hence, our proposed method quantitatively outperforms the block processing method. Besides, Table 4 lists the required computational time for performing the empirical mode decomposition directly on the original signal as well as that via the block processing method and our proposed method. Compared with the computational time for performing the empirical mode decomposition directly on the original signal, the required computational time of our proposed method is much smaller. Similarly, although the required computational time of our proposed method is a bit higher than that of the block processing method, our proposed method both qualitatively and quantitatively outperforms the block processing method.

Table 3 Errors of the approximated intrinsic mode functions (IMF) obtained by both our proposed method and the block processing method.

Methods	Proposed method	Block processing method
1st IMF	$0.466\text{x}10^{-2}$	$1.115\text{x}10^{-2}$
2nd IMF	$1.501\text{x}10^{-2}$	$3.324\text{x}10^{-2}$
3rd IMF	$4.515\text{x}10^{-2}$	$10.125\text{x}10^{-2}$
4th IMF	$13.067\text{x}10^{-2}$	$30.843\text{x}10^{-2}$
5th IMF	$15.232\text{x}10^{-2}$	$59.149\text{x}10^{-2}$

Table 4 Required computational time (in seconds) for performing the empirical mode decomposition (EMD) directly on the original signal as well as that via the block processing method and our proposed method.

Direct EMD	Block processing	Proposed method
0.333001	0.053585	0.114016

3.3 Example: Musical signal

In this example, a practical long musical signal is employed to demonstrate the effectiveness of our proposed method. The length of the original signal is 900000. The signal is represented by 20 polyphase components and the total number of the intrinsic mode functions are 8. Table 5 lists the errors of the intrinsic mode functions obtained by both our proposed method and the block processing method. In this example, it can be seen that the errors obtained by our proposed method in the first

Table 5 Errors of the approximated intrinsic mode functions (IMF) obtained by both our proposed method and the block processing method.

Methods	Proposed method	Block processing method
1th IMF	1.585x10^{-2}	0.576x10^{-2}
2th IMF	2.175x10^{-2}	1.058x10^{-2}
3th IMF	3.387x10^{-2}	1.673x10^{-2}
4th IMF	2.591x10^{-2}	2.687x10^{-2}
5th IMF	2.342x10^{-2}	3.441x10^{-2}
6th IMF	3.331x10^{-2}	5.350x10^{-2}
7th IMF	4.388x10^{-2}	8.651x10^{-2}
8th IMF	6.352x10^{-2}	13.722x10^{-2}

Table 6 Required computational time (in seconds) for performing the empirical mode decomposition (EMD) directly on the original signal as well as that via the block processing method and our proposed method.

Direct EMD	Block processing	Proposed method
1.4785	0.31485	0.51688

3 intrinsic mode functions are higher than those by the block processing method. This is because the errors due to the inconsistency between the consecutive blocks in the first three intrinsic mode functions are negligible. However, the errors from the 5th intrinsic mode function obtained by our proposed method are smaller than those obtained by the block processing method. Overall, our proposed method quantitatively outperforms the block processing method. Besides, Table 6 lists the required computational time for performing the empirical mode decomposition on the original signal as well as that via the block processing method and our proposed method. It can be seen that the required computational time of our proposed method is much lower than that for performing the empirical mode decomposition directly on the original signal. Similarly, although the required computational time of our proposed method is a bit higher than that of the block processing method, our proposed method both qualitatively and quantitatively outperforms the block processing method.

3.4 Example: Length of the day signal

In the last example, the signal on the length of the day covering the period from 1978 to 1988 studied by Huang et al [18] is employed for the illustration. The signal is shown in Fig. 7. Here, the length of the signal is 4000. It is represented by 4 polyphase components. The comparison is performed on the 6th intrinsic mode functions obtained by various methods. It can be clearly seen that the approximated intrinsic mode functions obtained via the block processing method is completely different from the true intrinsic mode function. On the other hand, the approximated intrinsic mode functions obtained by our proposed method is similar to the true intrinsic mode functions of the original signal. This implies that our proposed method qualitatively outperforms the block processing method for this real world signal. Table 7 lists the errors of the intrinsic mode functions obtained by both our proposed method and the block processing method. In this example, the total number of the intrinsic mode functions is 6. It can be shown that the errors obtained by our proposed method are lower than those obtained by the block processing method. Hence, our proposed method quantitatively outperforms the block processing method. Table 8 presents the required computational time for performing the empirical mode decomposition on the original signal for these three methods. The table shows that the required computational time of our proposed method is much lower than that for performing the empirical mode decomposition directly on the original signal. Similarly, although the required computational time of our proposed method is a bit higher than that of the block processing method, our proposed method both qualitatively and quantitatively outperforms the block processing method.

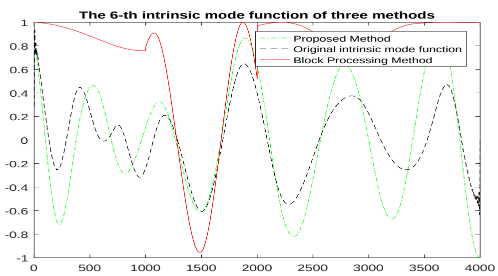

Fig. 7 *The 6th approximated intrinsic mode functions obtained by both our proposed method and the block processing method.*

Finally, our proposed method is compared with a fast empirical mode composition algorithm namely the UOAEMD [19]. For the UOAEMD, an unconstrained convex optimization approach is employed to obtain the intrinsic mode functions. Since it does not involve the interpolation and the iteration, this method greatly reduces the required computational time. In this example, the total number of the intrinsic mode functions is 7. Table 9 lists the errors of the first five intrinsic mode functions obtained by both the UOAEMD and our proposed method. It is clearly seen that the errors obtained

Table 7 Errors of the approximated intrinsic mode functions (IMF) obtained by both our proposed method and the block processing method.

Methods	Proposed method	Block processing method
1th IMF	$1.050 \text{x} 10^{-2}$	$2.263 \text{x} 10^{-2}$
2th IMF	$0.272 \text{x} 10^{-2}$	$0.857 \text{x} 10^{-2}$
3th IMF	$2.302 \text{x} 10^{-2}$	$4.004 \text{x} 10^{-2}$
4th IMF	$0.991 \text{x} 10^{-2}$	$7.334 \text{x} 10^{-2}$
5th IMF	$1.601 \text{x} 10^{-2}$	$13.606 \text{x} 10^{-2}$
6th IMF	$8.545 \text{x} 10^{-2}$	$90.530 \text{x} 10^{-2}$

Table 8 Required computational time (in seconds) for performing the empirical mode decomposition (EMD) directly on the original signal as well as that via the block processing method and our proposed method.

Direct EMD	Block processing	Proposed method
0.042101	0.017967	0.032493

Table 9 Errors of the intrinsic mode functions (IMF) obtained by both our proposed method and the UOAEMD.

Methods	Proposed method	UOAEMD
1th IMF	$1.050 \text{x} 10^{-2}$	$0.547 \text{x} 10^{-2}$
2th IMF	$0.272 \text{x} 10^{-2}$	$1.137 \text{x} 10^{-2}$
3th IMF	$2.302 \text{x} 10^{-2}$	$7.877 \text{x} 10^{-2}$
4th IMF	$0.991 \text{x} 10^{-2}$	$6.304 \text{x} 10^{-2}$
5th IMF	$1.601 \text{x} 10^{-2}$	$7.772 \text{x} 10^{-2}$

Table 10 Required computational time (in seconds) for both the UOAEMD and our proposed method.

UOAEMD	Proposed method
2.317578	0.032493

by the UOAEMD are larger than that obtained by our proposed method. Besides, Table 10 lists the required computational time of these two methods. It is worth noting that the UOAEMD is slower than the original empirical mode decomposition method. This is because it involves the matrix computation. Therefore, our proposed method outperforms the existing fast methods in terms of the required computational time and the errors of the intrinsic mode functions.

4 Conclusion

This paper proposes a parallel implementation of the empirical mode decomposition for nearly bandlimited signals via the polyphase representation. Compared with the block processing method, our proposed method outperforms both qualitatively and quantitatively. This is because our proposed method greatly reduces the boundary effect caused by the discontinuities between two consecutive blocks in the block processing method.

For the practical applications, the human signals such as the PPG, the ECG and the EEG signals are often acquired using the oversampling strategy. The polyphase components almost preserve the shape of the original signal. Also, as the energies of the nearly bandlimited signals are localized in the low frequency band, the lowpass filtering method would successfully suppress the oscillations generated by the differences among the intrinsic mode functions of the polyphase components. Hence, our proposed method achieves an excellent performance.

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