A method for extracting human gait series from accelerometer signals based on the ensemble empirical mode decomposition*

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In this paper, the ensemble empirical mode decomposition (EEMD) is applied to analyse accelerometer signals collected during normal human walking. First, the self-adaptive feature of EEMD is utilised to decompose the accelerometer signals, thus sifting out several intrinsic mode functions (IMFs) at disparate scales. Then, gait series can be extracted through peak detection from the eigen IMF that best represents gait rhythmicity. Compared with the method based on the empirical mode decomposition (EMD), the EEMD-based method has the following advantages: it remarkably improves the detection rate of peak values hidden in the original accelerometer signal, even when the signal is severely contaminated by the intermittent noises; this method effectively prevents the phenomenon of mode mixing found in the process of EMD. And a reasonable selection of parameters for the stop-filtering criteria can improve the calculation speed of the EEMD-based method. Meanwhile, the endpoint effect can be suppressed by using the auto regressive and moving average model to extend a short-time series in dual directions. The results suggest that EEMD is a powerful tool for extraction of gait rhythmicity and it also provides valuable clues for extracting eigen rhythm of other physiological signals.

Keywords: ensemble empirical mode decomposition, gait series, peak detection, intrinsic mode functions

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1. Introduction

The gait series is defined as the time intervals between the current step and next one during human walking.[1] As a vital output of non-stable physiological signals, a gait series hides much more information about our neuromuscular regulation.[2] Researchers also indicated that the rhythmicity of gait signals will be remarkably modified[3,4] due to the degeneration of human locomotor function and the appearance of nerve diseases. Therefore, one can not only obtain feature parameters that reflect physiological or pathological status of our locomotor system, but also further assess or model its function through the analysis of gait series.

Generally, a gait series can be formed in the following way: acquire the accelerometer signals dynamically during human walking, and then detect all the peaks in these signals.[5] This is because a peak value often occurs in the vertical direction when each foot contacts with the ground. Thus, if one can pick up every peak in a given time span, he could calculate the intervals between the strikes of each foot. And it is just these intervals that form the gait series for left or right foot. Therefore, it is reasonable to consider that peak detection is the key to and prerequisite of obtaining gait series from an original accelerometer signal with a high accuracy.[6]

Fourier transform and wavelet transform are generally considered to be mature tools for the signal analysis. However, although Fourier transform gives sharp identification in the frequency-domain, it cannot describe the time-domain features of signals at the same time. For the wavelet approach, different wavelet bases and decomposition levels must be artificially determined prior to the analysis, rendering it incapable of self-adaptive analysis for different signals.[7] On the contrary, the empirical mode decomposition (EMD) method, proposed by Huang *et al.* in 1998, depends solely on local characteristics of the data. It

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generates finite and often small number of intrinsic mode functions (IMFs) for multi-resolution analysis, yet requires not *a priori* basis. Given these merits, in recent years, EMD was extensively applied to the detection of signal trends, singular points and characteristic frequencies.[8−11] For instance, Liang *et al.* analysed the change of esophagus pressure using the EMD method.[12] Yet, it should be noted that a major drawback of the EMD method is mode mixing. To overcome this drawback, Wu and Huang proposed the ensemble empirical mode decomposition (EEMD) method in 2009.[13] This method utilises the Gaussian white noise, which has a unique uniform energy–frequency–time distribution in frequency-domain, to endow signals with continuity on different scales. In this manner, the EEMD method successfully prevents the aliasing in time-frequency distribution that is common in the EMD method, making it an effective tool in analysing non-linear and non-stationary signals.

This work attempts to pick up hidden gait rhythmicity from the accelerometer signals and detect the peaks from its eigen IMF using EEMD. Apart from eliminating the mode mixing phenomenon by introducing EEMD, this paper also probes into the selection of parameter for the stop-filtering criteria and elimination of the endpoint effect. Furthermore, traditional EMD algorithm was also applied to extract gait series from the same data as a comparison. Finally, we have discovered that extracting gait series based on the EEMD algorithm not merely shows higher detection rate, but also eliminates the errors to the maximum extent caused by mode mixing and endpoint effect. These merits of EEMD guarantee the accuracy of the extracted gait series, which is of vital importance for the follow-up analysis.

2. Basic theory of EEMD

2.1. Empirical mode decomposition

EMD regards any non-linear and non-stationary signals as the compound of some IMFs and a residue. An IMF is defined to satisfy two conditions:[14] (A) the number of extrema $N_{\rm e}$ and the number of zero crossings $N_{\rm z}$ must be either equal or differ at most by one; (B) at any point, the average of the upper envelope of the local maxima and lower envelope of the local minima is zero. If these two conditions are satisfied, the sifting process can be carried out as follows.

(i) Identify all the maxima and minima of $f(t)$ and fit the upper and lower envelopes $u_{\max}$ and $u_{\min}$ using the cubic spline function, thus obtain the curve of local mean $m(t) = (u_{\max} + u_{\min})/2$ as illustrated in Fig. 1. In this paper, the Roman italie g refers to the free-fall acceleration caused by gravity.

(ii) Remove the local mean $m(t)$ from its original signal $f(t)$, thus sifting out $h_1(t)$

$$h_1(t) = f(t) - m(t). \tag{1}$$

Examine whether $h_1(t)$ meets the above-mentioned two conditions for an IMF. If not, regard $h_1(t)$ as a new signal to be processed and repeat the above procedures till $h_1(t)$ becomes an IMF. Otherwise, $h_1(t)$ is defined as the first IMF and marked as $c_1(t)$

$$c_1(t) = h_1(t). \tag{2}$$

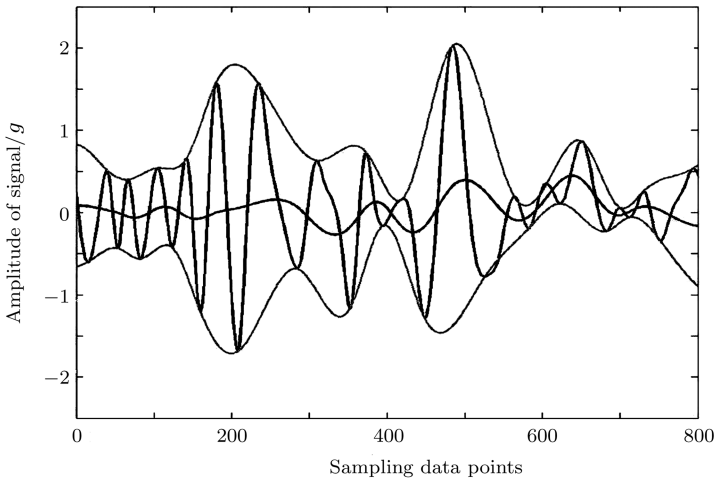


Fig. 1. The upper envelope, the lower envelope and their local mean.

(iii) After the first IMF is sifted out, it is removed from the original signal $f(t)$ in order to filter the residue $r_1(t)$

$$r_1(t) = f(t) - c_1(t). \tag{3}$$

At this time, regard the residue $r_1(t)$ as a new signal and repeat the above procedures for several times so as to sift out other IMFs. Once the extracted IMF meets the stop-filtering criteria, the decomposition will be automatically terminated. By then, $f(t)$ will be decomposed as

$$f(t) = \sum_{i=1}^{n} c_n(t) + r_n(t). \tag{4}$$

The above procedures suggest that EMD is capable of performing self-adaptive division on signal bandwidth according to its local features. And every sifting process generates one IMF that depicts signal detail and a low-frequency component that represents the trend of the signal. In other words, the bandwidth of an IMF is not artificially determined. Rather, it only depends on its local frequency span of the signal on every scale. These features enable EMD to perform a self-adaptive analysis on the non-linear and non-stationary signals.

However, when signals are contaminated by the intermittent noises, the EMD method is susceptible to mode mixing.[15] 'Mode mixing' is defined as any IMF including oscillations of disparate scales, or the signals of the same scale occur in different IMFs. When the extrema are not continuously and uniformly distributed in the original signal, errors may occur for curves fitting the upper and lower envelopes of the extrema, which will eventually lead to mode mixing. It is worth noting that mode mixing will not only pass on mode by mode, giving rise to distortion in the time-frequency distribution of different scales, but also deprive the IMF of its original physical meaning. As illustrated in Fig. 2, the symbol 'X' marks the spurious peaks caused by mode mixing in an IMF5 of the accelerometer signal.

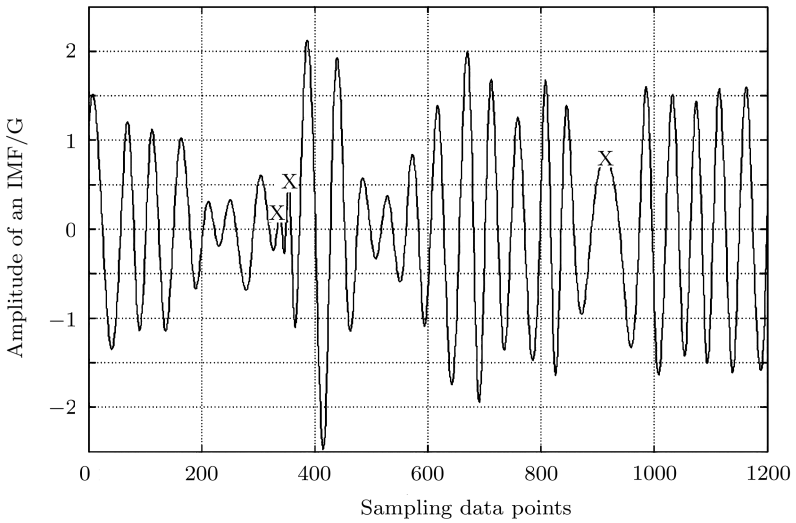


Fig. 2. The spurious peaks caused by mode mixing.

2.2. Ensemble empirical mode decomposition

EEMD is by its nature a noise-assisted method of signal processing. Taking advantages of the uniformly distributed frequency characteristic of Gaussian white noise, EEMD changes the distribution feature of the signal on disparate scales. In this way, the results of EEMD are devoid of mode mixing. The sifting processes are shown as follows:

(i) Add to the signal $f(t)$ an ensemble of n groups of Gaussian white noise $n(t)$, of which the mean value is zero and standard deviation of amplitude is a constant. If $f_i(t)$ indicates the ith group of noise-added signal, and $n_i(t)$ the ith group of Gaussian white noise signals added, their relation is shown as follows:

$$f_i(t) = f(t) + n_i(t). \tag{5}$$

(ii) Decompose every group of $f_i(t)$ using the

EMD method. Then average the ensemble of all noise-added IMFs and define the mean value of ensemble as the final EEMD. Since the fitting error generated by the white noise on disparate scales can be reduced by averaging the ensemble of IMFs, the only persistent part that survives the whole averaging process is the signal itself. The white noise, however, merely serves as a uniform reference frame in the time-frequency space. Using the EEMD method, one can capture signals of the same scale without needing any *a priori*. Thus, the EEMD method stands for a major improvement over the original EMD method.

To improve the quality of the EEMD in practical manipulation, we should also consider in detail the ratio of the standard deviation of the added noise to that of the original signal, as well as the total number of ensemble. Considering the ratio, on one hand, the added Gaussian white noise should not affect the extrema distribution of the original high-frequency components in the signal. On the other hand, however, it must change the extrema distribution of the low-frequency components. As for the number of ensemble, since the random error generated by the added noise will cancel out each other in the ensemble mean, the more the groups of added noise are, the closer the results are to actual signals. Of course, increasing the number of ensemble will no doubt lead to the increase in the time complexity of algorithm. To quantitatively measure the decomposition error ε_n of EEMD, Wu and Huang[13] proposed an empirical method

$$\varepsilon_n = \varepsilon/\sqrt{n}\ , \tag{6}$$

where ε denotes the ratio of the standard deviation of the Gaussian white noise amplitude to that of the original signal amplitude, and n is the group number of the added Gaussian white noises. Considering the feature of the accelerometer signals from human walking, when $\varepsilon = 0.15$ and $n = 100$, EEMD can most effectively eliminate mode mixing in the sifting process. Figure 3 shows the wave form of IMF5 that is obtained using the above parameters. Compared with Fig. 2, there are no spurious peaks in the wave form of IMF5.

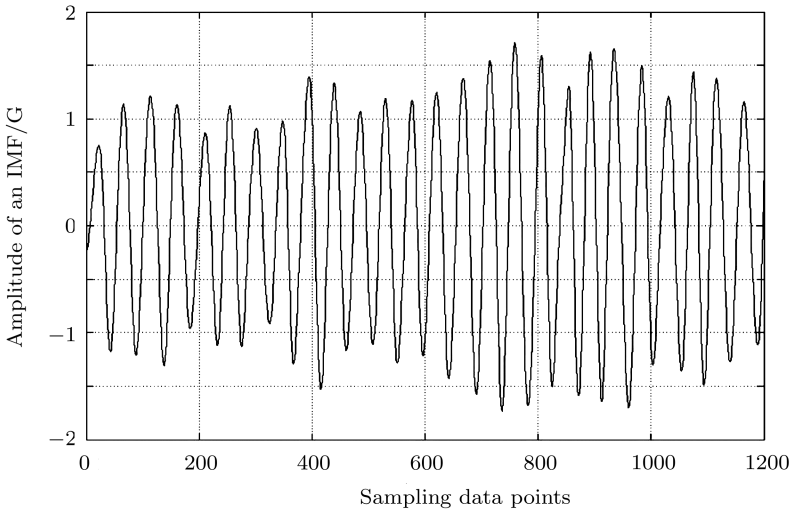


Fig. 3. An IMF5 obtained by the EEMD method.

3. Experiment method

3.1. Subjects and experimental data

The accelerometer signals collected under normal walking were provided by Mitsubishi Chemical Group Science and Technology Research Center, Inc. in this research. The subjects consist of 20 cases, including 12 males and 8 females. The age ranges from 48 to 71 years, the mean value of which is 65.32±5.25 years (average ± standard deviation). All cases are healthy, devoid of nervous, respiratory and heart diseases. Experimental data were obtained after all the subjects have a good knowledge of their situation and their informed consents signed. Also, the subjects did not take any medicine during a period of time prior to the measurements.

A three-dimensional accelerometer was attached to the waist of the subjects in a regulated direction in order to guarantee that normal walking was not affected. The accelerometer automatically recorded the accelerometer signals from the subjects in X, Y and Z directions. The sampling frequency for every channel is 100 Hz. The A/D converter is 10 bit and its measuring range is ± 50 m/s^2. A sample file was automatically generated every 10 min. All the subjects were requested to walk for 1 h on a flat ground. The collected data were preprocessed by a 0.2–35 Hz bandpass filter to eliminate static accelerometer signal and high frequency noises as well.

3.2. Extracting gait series using the EEMD method

Process the original accelerometer signal using the EEMD method, from which one can sift out the eigen IMF that contains most energy of the peaks in the signal. When the eigen IMF is determined, we can detect each maximum in the IMF and identify the time when each maximum occurs using the threshold-screening method.[16] As illustrated in Fig. 4, the symbol '•' is used to mark the peaks of the accelerometer signal formed when either feet strikes the ground. If one calculates any time interval between each current step and next one for the same foot, gait series for right

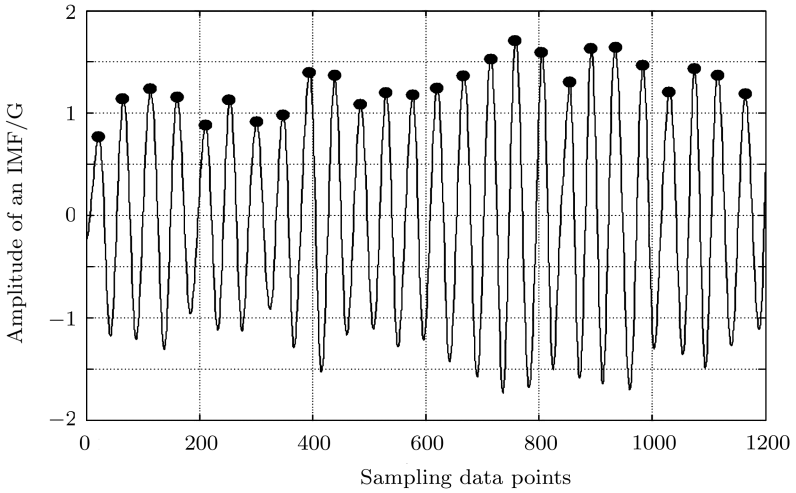


Fig. 4. Extracting gait series from an IMF5 using the EEMD method.

foot or left one will be obtained. As illustrated in Fig. 4, after the accelerometer signals are processed using EEMD, the peaks are pronounced in the IMF5, devoid of any interference from noise and other frequency components.

3.3. Stop-filtering criteria

When each IMF is extracted using EEMD method, if the extracted IMF satisfies one of the following two stop-filtering criteria, the sifting process will be automatically terminated: (i) the amplitude of the extracted IMF is less than the screening threshold value; (ii) the residue $r_n(t)$ becomes a monotonic function and no IMF can be filtered any more. Certainly, it is difficult to guarantee that the local mean value of the IMF equals absolutely to zero in practical operations. However, if the above two stop-filtering criteria are used to screen out an IMF, a large number of redundant extractions will be generated, and the actual physical meaning of the extracted IMF will be lost. Thus, it is possible to terminate the extraction of the IMF using the following criterion

$$S_d = \sum_{t=0}^{T} \frac{|\mathrm{IMF}_{n-1}(t) - \mathrm{IMF}_n(t)|2'}{\mathrm{IMF}_n^2(t)}, \qquad (7)$$

where S_d is the standard variant of two adjacent intrinsic mode functions $\mathrm{IMF}_{n-1}(t)$ and $\mathrm{IMF}_n(t)$; T is the sampling length of the signal. By computing S_d, one can measure the degree of discretion in two given adjacent IMFs. When S_d is lower than the screening threshold, it can automatically terminate further

IMF extraction. After repeated tests, the S_d threshold suitable for the extraction of gait series is set to about 0.15.

3.4. Endpoint effect phenomenon

When the data length of the accelerometer signal collected from experiments is very short, the accuracy of curve fitting is especially susceptible to the endpoint effect in the EEMD method. The endpoint effect is defined as the envelope of the interpolated values, which deviates from that of the true signal in a short-time series. This effect is mainly brought about by the uncertain fitting points of the spline function in the vicinity of two endpoints. When the cubic spline function is used for curve fitting, there exists severe distortion in the envelopes of minima and maxima on the fitted curve. In Fig. 5(a), the IMF2 is the first 40 points of that extracted from an accelerometer signal with a total length of 30000 points, whereas in Fig. 5(b), the IMF2 is extracted from a very short signal, that is, the first 40 points of the same accelerometer signal as used in Fig. 5(a).

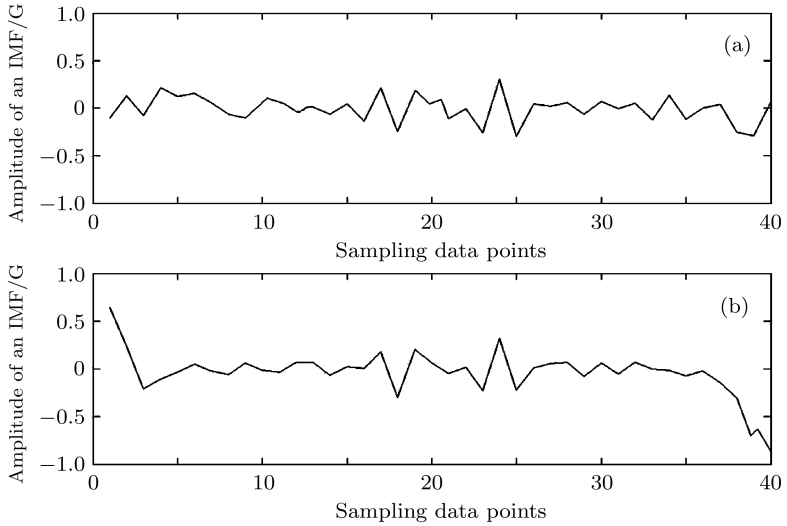


Fig. 5. The endpoint effect.

From the two figures above, it is reasonable to regard the extracted IMF2 from a 30000 point series as the 'standard' IMF in terms of the sufficient data length. By contrast, when the length of a series is shortened to merely 40 points, the endpoint effect results in severe divergence of the envelope in the close vicinity of both endpoints. If one further decomposes the IMF2 contaminated by the endpoint effect, he will merely end up with highly unreliable results since the distortion will pass on mode by mode.

3.5. Eliminating endpoint effect using ARMA model

The endpoint effect is mainly caused by the limited data length of the decomposed signal. Hence, the key to eliminating this phenomenon lies in extending data length to a greater level while preserving its feature of the original signal. The auto regressive and moving average (ARMA) model can set up a mathematical model according to the given data set and extend data length by predicting the signal trend using the established model. Therefore, this paper tries to extend the length of short accelerometer signal by performing model recognition, parameter estimation and model examination through ARMA model, so as to restrain the endpoint effect during the sifting process in an effective way. The major procedures for such a bidirectional extension are as follows.

(i) Data stabilisation: generally AR, MA and ARMA models are used to describe a stable time series, but the accelerometer signal is a typical sort of nonstable and non-linear signal. Therefore, the accelerometer signal must be preprocessed with the zero-equalisation and stabilisation manipulation before ARMA model is applied.

(ii) Model recognition: perform the correlation analysis on the accelerometer signals with 95% confi-

dence, both the obtained autocorrelation and partial autocorrelation functions display a tailed distribution, thus ARMA model is the best model for describing the signals.

(iii) Parameter estimation and model examination: fit a series of ARMA (p, q) models for the accelerometer signals, complete the identification for the function order using the AIC rule, and determine whether the residue is white noise according to the autocorrelation test and the cross-correlation test on errors.

After a proper ARMA model is established for the accelerometer signal, one can perform a bidirectional prediction for it. To validate its accuracy of the model, intercept 100 sampling points from an original signal series, as illustrated in Fig. 6(a), then extend 100 data points in either direction for the intercepted series using ARMA model, as shown in Fig. 6(b). For comparison, we illustrate the original 300-point data in Fig. 6(c).

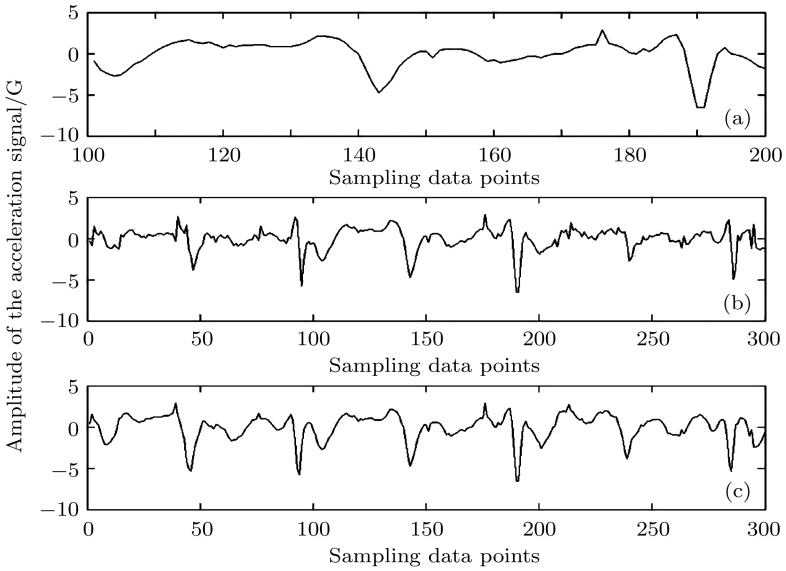


Fig. 6. Performing a bidirectional extension using ARMA model.

As illustrated in Fig. 6, compared with the true signal, its extension signal predicted by ARMA model can not only recur the gait cycle, but also accurately depict the peaks, valleys, and its fluctuations of the actual signals. Thus, extension version generated from the ARMA model lays a good foundation for the next accurate detection of peaks. To quantitatively measure the prediction error, EEMD is used to extract peaks for both the true signals and its extension version. The prediction error ΔN is defined as follows:

$$\Delta N = \frac{1}{N}\sum_{n=1}^{N}\frac{|\mathrm{IMF5}_n^{\mathrm{e}} - \mathrm{IMF5}_n^{\mathrm{o}}|^2}{(\mathrm{IMF5}_n^{\mathrm{o}})^2}, \qquad (8)$$

where N is the series length, here $N = 300$, $\mathrm{IMF5}_n^{\mathrm{e}}$ indicates IMF5 of the extended signal, and $\mathrm{IMF5}_n^{\mathrm{o}}$ indicates IMF5 of the true signal. The resulting ΔN is less than 1×10^{-2}. In other words, the ARMA-assisted extended signal not only remains the characteristic of original accelerometer signal, but also suppresses the endpoint effect generated in the sifting process.

4. Results

Since accelerometer signals in the vertical direction (Y axis) is closely associated with gait rhythmicity when the subjects are walking,[17] we only take the Y-axis signals stored in the sample files for analysis. According to the feature of gait rhythmicity during walking, we decompose the accelerometer signals at disparate scales using EEMD and detect each peak in the screened IMF. The numbers of both missing identification and false identification are counted and listed in Table 1. For comparison, the similar results obtained from EMD method are also listed in Table 2.

Table 1. The EEMD-based peak detection results.

data No.	total peaks	false identification	missing identification	detection rate/%
d080111	633	5	1	99.05
d080117	617	6	2	98.70
d080225	636	3	1	99.37
d080228	606	5	0	99.17
d080305	685	3	2	99.27
d080307	663	3	0	99.55
d080402	639	3	1	99.37
d080415	619	4	0	99.35
d080509	627	5	2	98.88
d080603	731	3	6	98.76
d080617	717	2	5	99.02
d080711	725	4	1	99.31
d080722	647	2	2	99.38
d080801	623	0	1	99.84
d080816	657	2	4	99.09
d080911	639	2	2	99.37
d080921	646	3	2	99.23
d081021	641	1	2	99.53
d081127	659	3	2	99.24
d081213	655	3	3	99.08
mean ± standard deviation	653.25±35.61	3.10±1.44	1.95±1.57	99.23±0.27

Table 2. The EMD-based peak detection results.

data No.	total peaks	false identification	missing identification	detection rate/%
d080111	633	11	1	98.10
d080117	617	14	3	97.24
d080225	636	5	0	99.21
d080228	606	7	1	98.68
d080305	685	9	2	98.39
d080307	663	8	4	98.19
d080402	639	5	3	98.75
d080415	619	3	1	99.35
d080509	627	10	3	97.93
d080603	731	14	1	97.95
d080617	717	11	2	98.19
d080711	725	10	1	98.48
d080722	647	5	4	98.61
d080801	623	9	2	98.23
d080816	657	10	2	98.17
d080911	639	5	2	98.90
d080921	646	12	0	98.14
d081021	641	15	3	97.19
d081127	659	7	4	98.33
d081213	655	11	1	98.02
mean ± standard deviation	653.25±35.61	9.05±3.39	2.00±1.26	98.30±0.54

From the statistics in Tables 1 and 2, the detection rate for peak values in accelerometer signals is 99.23%±0.27% for EEMD method, among which the number of false identification is 3.10±1.44, and the number of missing identification is 1.95±1.57. However, the detection rate for peak values in the same accelerometer signals is 98.30%±0.54% for EMD method, among which the number of false identification is 9.05±3.39, and the number of missing identification is 2.00±1.26.

A two-tailed t test on the detection rate of the EEMD and EMD methods is applied for a statistical significance. The result of t test shows that P value is less than 0.05, which suggests a remarkable distinction between statistical data obtained from the two methods. The statistical analysis indicates that, compared with traditional EMD-based method, the EEMD-based one guarantees a higher detection rate and reduces the amount of false identification and missing identification. It is of vital importance for accurately extracting gait series and performing the follow-up analysis.

5. Conclusions

Since gait rhythmicity is an important aspect in reflecting the locomotor system of the human body, deriving the gait series from the original accelerometer signals accurately is indispensable for the assessment of the locomotion ability and mathematical modeling for our motor nerve system. In this manner, this research mainly attempts to decompose the accelerometer signal utilising the EEMD method. Once the optimal decomposition scale is determined, the gait series of the left and right foot can be accurately picked up from the eigen IMF which contains most energy of gait rhythmicity. In addition, this research also discusses how to address mode mixing commonly occurring during the decomposition and stop IMF filtering by selecting proper parameters, which improves the reliability of the results and speeds up the computation process. Finally, concerning the endpoint effect that will occur especially when the decomposition is applied to short-time signals, this paper also proposes a solution that extends signal length through bidirectional prediction using the ARMA model.

As a comparison, this paper also applies the traditional EMD method to extract gait series. Since the accelerometer signals are often exposed to strong intermittent noises, the accuracy is susceptible to the interference from mode mixing and endpoint effect when EMD-based method is applied to extract peaks from the sifted eigen IMF. This disturbance often leads to false identification or missing identification of the peaks, which may severely affect the reliability if one further derives dynamical parameters from the extracted gait series.

Therefore, it can be deduced from the results that, even if severe intermittent noises exists in human accelerometer signals, the EEMD-based method will still pick up peaks with very high accuracy and efficiency. This method can serve as a substitute for the EMD-based method, since it successfully prevents the phenomenon of mode mixing. The extracted peaks by the EEMD-based method not merely reflects gait rhythmicity and variation trend of the signal, but the algorithm itself also shows great robustness. Furthermore, a bidirectional extension of accelerometer signals based on the ARMA model can remarkably restrain the waveform distortion resulting from the endpoint effect. Even when such a model is applied to the processing of short-time signals, peaks can still be accurately positioned. Finally, reasonable selection of the parameters for the stop-filtering criteria can accelerate the computation process of the peak detection algorithm. In conclusion, this paper proves that EEMD is a powerful tool for extraction of gait rhythmicity, and it also provides valuable clues for extracting characteristic rhythm of other physiological signals.

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