

Identification of the Slow Wave of Bowel Myoelectrical Surface Recording by Empirical Mode Decomposition

Yiyao Ye, J. Garcia-Casado, J.L. Martinez-de-Juan, J.L. Guardiola, and J.L. Ponce

Abstract—Surface electroenterogram (EEnG) is a non-invasive method to study bowel myoelectrical activity. Nevertheless, surface recorded EEnG is contaminated by respiratory, motion artifacts, and other interferences. The goal of this paper is to remove the respiration artifact and ultra-low frequency components from surface EEnG by means of empirical mode decomposition (EMD). Seven recording sessions on abdominal surface of three Beagle dogs were conducted. Power percentages of interferences and of fundamental slow wave were calculated before and after the application of the method. The results show that the interference power is significantly reduced ($23\pm 16\%$ vs. $5\pm 4\%$), and fundamental slow wave power is significantly increased ($59\pm 17\%$ vs. $76\pm 13\%$). Therefore, the EMD method can be helpful to remove respiration and ultra-low frequency components from the external EEnG recordings.

I. INTRODUCTION

THE myoelectrical signal recorded from small bowel serosa is known as electroenterogram (EEnG). The relationship between myoelectric activity and mechanical activity of small bowel is widely accepted [1].

The EEnG is composed of slow waves (SW) and spike burst (SB). The former is a peacemaker activity that does not represent intestinal motility but the maximum rhythm of bowel contractions. The latter only appears when the smooth muscle contracts and indicates moving activity.

However, the application of internal myoelectric techniques for clinical purposes is restrained because surgery is required for electrode implantation. It has been proved that surface recording of EEnG could be used for non-invasive monitoring of intestinal motility in animal model [2].

The major disadvantage of surface recording is not the low amplitude of the signal, but the strong interferences such as respiratory, movement artifacts, cardiac signals and other interferences. The SW frequency of the intestinal signal is around 18 cycles/min (18 cpm, 0.3 Hz) in dogs, whereas the frequency of respiratory artifact is about 0.2-0.4

Hz. In addition, frequency spectra of external signal often shows an exponential increase of power towards the very low frequency range [3]. Its possible sources are low-frequency drifts and movement artifacts consisting of sudden upward or downward deflections of the recorded potential [3]. These artifacts can affect the signal power spectral density (PSD), which can cause misinterpretation of the analysis. So it is necessary to have an appropriate artifact reduction method for the EEnG analysis.

In this paper, a general data analysis method, empirical mode decomposition (EMD) [4], is used for removing the respiration artifact and ultra-low frequency components from cutaneous EEnG recording.

II. MATERIAL AND METHODS

A. Signal acquisition

Seven recording sessions were carried out in three Beagle dogs in fasting state for more than twelve hours. The dogs were anesthetized, and the respiration was fixed to 27 cpm (0.45 Hz). Bipolar external signal was recorded by two Ag-AgCl monopolar electrodes placed on the abdominal skin. The electrodes were positioned symmetrically respect to longitudinal axis of the animal. Inter-electrode distance was set to 2 cm.

The signal was amplified and band-pass filtered with a bandwidth of [0.05 Hz, 35 Hz]. Finally, signal was acquired with a sample rate of 100 Hz.

B. Preprocessing

In this work, we focus on the interferences that affect low frequencies, i.e. slow wave band. Therefore, every minute of surface recorded EEnG was digitally filtered (low pass cut-off 2 Hz), because energy associated to the slow wave is concentrated below 2 Hz [1]-[2].

Afterward, a pre-processing procedure based on agglomerative hierarchical clustering [5] was used to remove motion-artifacted segments before the application of the EMD method. The simplest way to test whether there are anomalous local extreme, is to obtain a partition of two clusters. If the centroid of the two clusters has significant differences, then it is considered there is a sudden upward or downward deflection of the signal. Once the anomalous local extremes are detected, they were replaced by the maximum value of the EEnG without motion artifact. Subsequently cubic spline interpolation was used to reconstruct the EEnG segments with motion artifacts.

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C. Empirical mode decomposition (EMD)

The pretreated signal was subsequently processed by means of EMD method. The EMD method consists in decomposing a time series into a finite and often small number of intrinsic mode functions (IMFs) [4]. The IMFs are nonlinear functions which can be extracted directly from the data. The decomposition procedure is adaptive and data-driven, which is suitable for analyzing nonlinear and non-stationary data. A signal must satisfy two criteria to be an IMF: first, the number of extreme and the number of zero-crossings must differ at most by one, and second, the mean of its upper and lower envelopes must be almost zero.

The amplitude of this mean can be compared with the amplitude of the corresponding mode. However, this can lead to over-decomposition [6]. In this paper, a criterion based on 2 thresholds θ_1 and θ_2 was used, which was initially proposed in [6]. The aim of this criterion is to guarantee global small fluctuations in the mean, while allowing local large excursions. In this work, the parameters were set to: $\alpha=0.05$, $\theta_1=0.05$ and $\theta_2=0.5$.

The next step is to identify which IMFs correspond to artifacts or interferences in order to remove them from the signal. For this purpose, each IMF was analyzed in frequency domain. Specifically Hamming window periodogram was employed and dominant frequency and mean frequency of each IMF was calculated.

Due to the fact that slow wave energy is between 0.15 and 2 Hz [2], and the respiration was fixed to 0.45 Hz, we consider that an IMF is interference if its dominant frequency and mean frequency are between 0.43-0.47 Hz or below 0.15 Hz.

D. Quantification of the method

Finally, power percentages of interferences and of fundamental slow wave were calculated before and after the application of the method. Interference power (P_1) and fundamental slow wave power (P_2) were obtained using (1):

$$P_1 = \frac{\sum_{f=0}^{f=0.15} \text{PSD}[f_k] + \sum_{f=0.43}^{f=0.47} \text{PSD}[f_k]}{\sum_{f=0}^{f=2} \text{PSD}[f_k]}; \quad P_2 = \frac{\sum_{f=0.15}^{f=0.35} \text{PSD}[f_k]}{\sum_{f=0}^{f=2} \text{PSD}[f_k]} \quad (1)$$

III. RESULTS

Fig. 1a) shows one minute of myoelectric signal with strong respiratory interference. Its spectrum can be observed in Fig. 1b). The EMD method yields five IMF components and a residue as shown in Fig. 2. As we can see, the first component corresponds to the fastest time variation of data. As the decomposition process proceeds, the mean frequency of the mode decreases.

The dominant frequency and mean frequency of the second IMF (IMF2) are 0.45 Hz and 0.448 Hz respectively, so we can deduce that this component corresponds to

respiratory artifact. On the other hand, IMF4 and IMF5 correspond to ultra-low frequency components since in both cases the dominant frequency and mean frequency are below 0.15 Hz. Finally, component 3 (IMF3) and component 1 (IMF1) are ongoing intestinal slow wave around 12 cpm and harmonic signal respectively. Fig. 1c) and Fig. 1d) show the extracted signal (sum of IMF1 and IMF3) and its spectrum. It can be observed that the frequency content corresponding to respiratory artifact was greatly reduced and the myoelectric signal component is effectively extracted.

Fig. 3a) shows another example of the applied method to remove interferences on surface EEnG. In this case, strong ultra-low frequency components can be appreciated (see Fig. 3b). Fig. 4 shows the corresponding decomposition in IMFs. Spectral analysis indicates that the last two components (IMF4 and IMF5) contribute to the ultra-low frequency contents of the signal. And therefore, they should not be included in the output signal. The residue is apparently the trend in the data. The resulting signal and its spectrum are shown in Fig. 3c) and 3d). It can be observed that the ultra-low frequency components were greatly reduced.

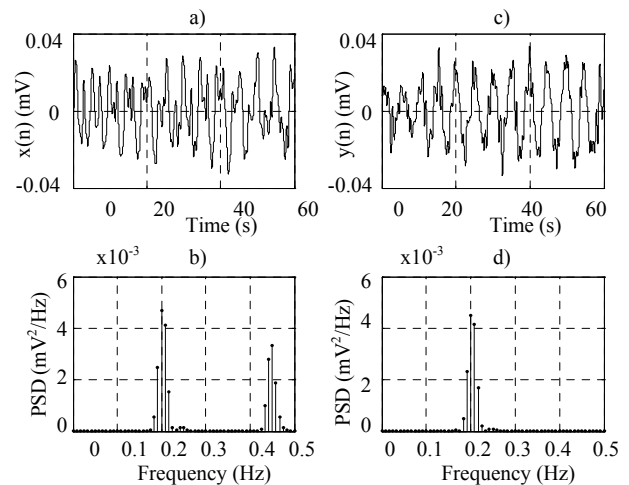


Fig. 1. a) One minute of surface EEnG $x(n)$. b) Periodogram of $x(n)$. c) Processed signal $y(n)$ by means of EMD method. d) Periodogram of $y(n)$.

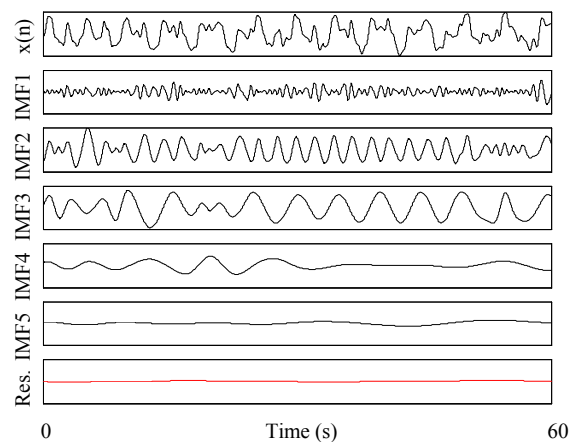


Fig. 2. Decomposition of surface EEnG $x(n)$ shown in Fig. 1a) using EMD.

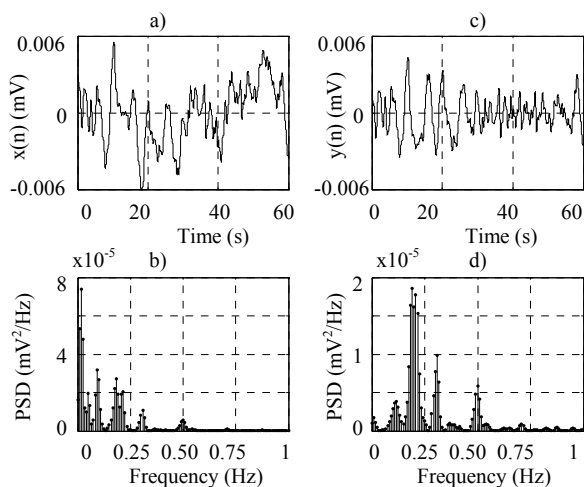


Fig. 3. a) One minute of surface EEnG $x(n)$. b) Periodogram of $x(n)$. c) Processed signal $y(n)$ by means of EMD method. d) Periodogram of $y(n)$.

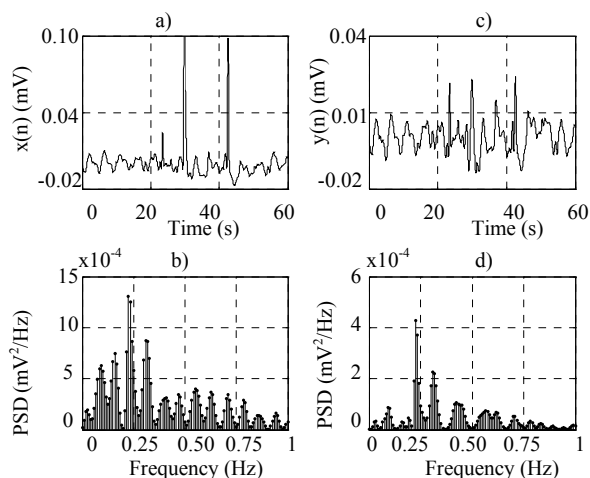


Fig. 5. a) One minute of surface EEnG $x(n)$. b) Periodogram of $x(n)$. c) Processed signal $y(n)$ by means of EMD method. d) Periodogram of $y(n)$.

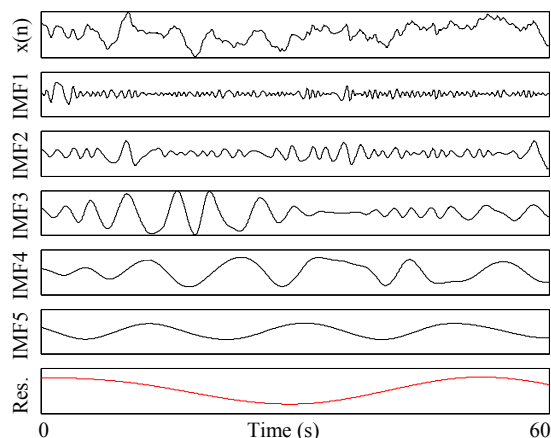


Fig. 4. Decomposition of surface EEnG $x(n)$ shown in Fig. 3a using EMD.

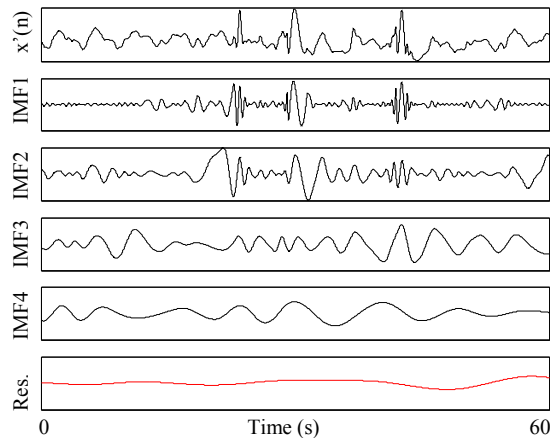


Fig. 6. Decomposition of pretreated surface EEnG $x'(n)$ using EMD.

In the third example, one minute of EEnG recording with strong motion interference (seconds 30 and 42 in Fig. 5a) was used. Cluster analysis could identify the sudden upward deflection of the signal and the pretreated signal $x'(n)$ is shown in Fig. 6. Again, the last component (IMF4) of Fig. 6 was removed from the original signal after spectral analysis since it corresponds to ultra-low frequency components. Fig. 5c) shows the resulting signal. Fig. 5b) and 5d) show the frequency content of the original signal and the processed signal. It can be observed that the combined method of cluster analysis and EMD can effectively remove the motion artifact and the low-frequency drifts.

Table I show the statistics of the two indicators (P_1 and P_2) before and after the application of the method. N is the number of processed minutes in each session. The last row indicates the global mean and standard deviation of P_1 and P_2 . It can be seen that interference power (P_1) is significantly reduced from 23% to 5% (t-test, $p < 0.05$), whereas fundamental slow wave power (P_2) is significantly increased from 59% to 76% (t-test, $p < 0.05$).

IV. DISCUSSION

Surface EEnG recording is very attractive due to its non-invasiveness. One of the main problems of the EEnG is the poor quality of the recording: the weakness of the myoelectric signal and the strong interferences, such as ECG, respiratory, and motion artifact. Several methods have been applied to improve the quality of the surface myoelectrical recording, including adaptive filtering [7], and blind source separation (BSS) [8].

Table I. Mean and standard deviation of the two indicators (P_1 and P_2), before and after the application of the EMD method.

Session	N	Original EEnG ($\mu \pm \sigma$)		Processed signal ($\mu \pm \sigma$)	
		P_1 (%)	P_2 (%)	P_1 (%)	P_2 (%)
1	74	47±14	37±17	3±4	73±12
2	67	24±12	54±18	3±3	76±13
3	185	22±20	51±20	3±3	69±15
4	156	23±19	61±20	6±5	75±16
5	129	18±12	58±16	4±5	81±12
6	281	19±14	71±13	7±6	82±8
7	233	22±16	58±19	5±4	73±17
	1125	23±16	59±17	5±4	76±13

An inherent weakness of adaptive filtering techniques is that it requires a reference signal that is strongly correlated with the various artifacts to be removed. Sometimes it is difficult to obtain such a reference signal.

On the other hand, the use of the BSS method in order to remove artifacts implies multichannel surface EEnG recordings. But in our case, the number of channels is constrained due to the electrodes recording area. When only a few channels are available, this method concentrates the artifact to be removed in one of the output signals [8]. In addition, in order to use the BSS method, the artifact to be removed should be recorded in more than two channels simultaneously.

In this paper, a time-domain data analysis method – EMD was used to remove artifacts from surface EEnG recording. In contrast to BSS, the EMD method only requires one signal channel to be recorded. Nevertheless, the EMD method presents also some disadvantages. The major disadvantage is that the presence of the confusion frequency band [6]. That is, two signals with similar frequency can not be separated by this method. This can lead to a situation, in which the artifact to be removed can not be correctly extracted from surface recorded EEnG. Another drawback is the boundary conditions due to finite observation lengths. In this paper, mirrorizing the extreme close to the edges proposed in [6] was used to minimize this error.

When the myoelectrical signal is embedded in strong motion artifacts, a pre-processing of the data may be necessary. This is because the EMD method is based on the identification of scale from successive extremes [4]. A hard-threshold is used for recovery of gastric slow wave when strong motion artifacts are present [9]. In this paper, a pre-processing procedure based on agglomerative hierarchical clustering is introduced to automatically identify the motion artifacts in the data. In the hard-threshold method, the motion-artifacted segment is flattened, whereas in this paper this segment is smoothly replaced using cubic spline.

In contrast to dominant and mean frequency calculated from periodogram, other authors defend the use of instantaneous frequency derived from the Hilbert transform to identify the interference on the IMFs [9]. Theoretically, an IMF is almost symmetric, and hence should present a unique local frequency. In other words, the instantaneous frequency of the different IMFs may fluctuate around a narrow frequency range. However, we found that spectral analysis is also adequate for this purpose.

In this work, the respiration of the animal was fixed to 27 cpm. However, in physiologic conditions the breathing frequency varies throughout the recording session. This could make more difficult the procedure of the identification of the respiratory artifact on the different IMFs. In this sense, simultaneous recording of breathing could be helpful to identify respiration in IMFs.

As it can be observed in the presented results, the

respiratory artifacts and ultra-low frequency components were successfully removed by means of EMD method. This result is in agreement with other authors, who used this technique for artifact reduction in a similar signal as the electrogastrogram (EGG) [9]. In addition, they defend that the ECG activity can also be extracted from cutaneous EGG using EMD [9]. In our case, this could be applied to remove the ECG interference on EEnG which mainly affects higher frequencies (i.e., spike burst band).

V. CONCLUSION

Experimental results show that the respiratory, ultra-low frequency components could be removed from surface EEnG recording by means of EMD method and a pre-processing procedure based on agglomerative hierarchical clustering.

This can be very useful in order to enhance the quality of surface EEnG recordings and to monitor non-invasively the intestinal slow wave.

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