

Detection technique of muscle activation intervals for sEMG signals based on the Empirical Mode Decomposition

Junghoon Lee, Hyunchul Ko, Seunghwan Lee, Hyunsook Lee, Youngro Yoon

Abstract— The best way to detect the onset and offset time of muscle activation is through visual decision making by clinical experts like physical therapists. Humans can recognize muscle activation trends recorded from surface EMG signals. Current computer-based algorithms are being researched toward yielding similar results by clinical experts. A new algorithm in this paper has the ability, like humans, to recognize a trend from noisy input signals. We propose using the Empirical Mode Decomposition (EMD), because it is effectual to recognize trends which are decomposed by Hilbert transform and synthesized of Intrinsic Mode Functions (IMFs). These synthesized functions represent hidden low-frequency trends according to more iterative processes. Iterations will be stopped at the minimum SD of a resting period of EMG signals. The proposed method is very useful and easy implemented, but there are some limitations. The EMD method is only available on an off-line data and requires relatively high computational performances to find the IMFs. To use the proposed method, it is possible to detect muscle activation intervals of sEMG signals.

I. INTRODUCTION

THE surface electromyography (EMG) signal is widely used as a suitable means to analyze physiological processes involved in producing joint movements.[1] Surface EMG is a very convenient trigger source in muscle-machine interface, because it is easier to record it than the needle-electrode EMG. Some applications of surface EMG are useful to control rehabilitation devices or to study the biomechanics and motor control of the muscular-skeletal system during different movements of the legs and arms. [2]

The onset and the offset (termination) time of muscle activation are essential variables in research fields of surface EMG. The best way to detect the onset and the offset time of muscle activation is through visual detection by clinical experts like physical therapists. Visual detection is referred to as being a golden-standard in this area. Therefore, computer-based algorithms are tried to detect the exact onset and the offset time similar to human perception.

In 1987, Richard P. Di Fabio developed the first computer-based algorithm to detect the onset time. [3] It was based on a threshold depending on EMG signals received during muscle relaxations. After Di Fabio, some techniques have been proposed to detect the onset alone or alternatively,

the intervals of muscle activation. [4,5,6,7,8] Most of the techniques commit errors when spike noises or white noises are mixed with EMG signals. On the other hand, human observation can recognize the trend of muscle activation although there are a lot of noises. A new technique discussed in this paper, must have this kind of ability to withstand noisy signals. That is, the new technique should be able to extract contraction-relaxation trends without interference.

In this research, we propose to find the muscle contraction-relaxation trends by using the EMD method and detect an onset or offset time. The EMD method can decompose an input signal to some intrinsic mode functions[9,10]. For applying the EMD method, a stop condition value is typically set to 0.3 in standard deviation (SD). And we evaluate the method comparing with Di Fabio's method[3] and the integrated profile (IP) method.[11]

II. METHOD

A. Data acquisition and pre-processing

The EMG signals are recorded on the biceps brachii muscle using MP150 system which is produced by the BioPac company. Ground for differential amplification is located at the wrist of the same arm. To minimize skin impedance, the surface EMG electrodes are attached to the points of skin after careful cleaning dominant arm of a subject who is selected and fixed on a table with a height up to his chest. The subjects lift and release their fixed arms repetitively and freely. The experiment lasts for about one minute and the sampling frequency is 10 kHz. In consideration of a computational power, single activation interval was selected and down-sampled up to 100 Hz and finally all of signals are rectified.

The subjects are 31 persons with no abnormalities in their arms or contraction muscles. Their mean age is 26.5 years old (the youngest subject is 21 years old and the oldest subject is 33 years old), and the standard deviation is 2.4 years old. All of the subjects are men who don't have any experiences of surgical treatments.[15] Before the start of their experiments, they fully understood what they were about to do. To increase accuracy, preliminary experiments are performed at least once.

B. The EMD process

Figure 1 shows a flowchart of the proposed method. To apply the EMD method, a stop condition is defined that the SD of IMF is less than 0.3. Hilbert transform, the

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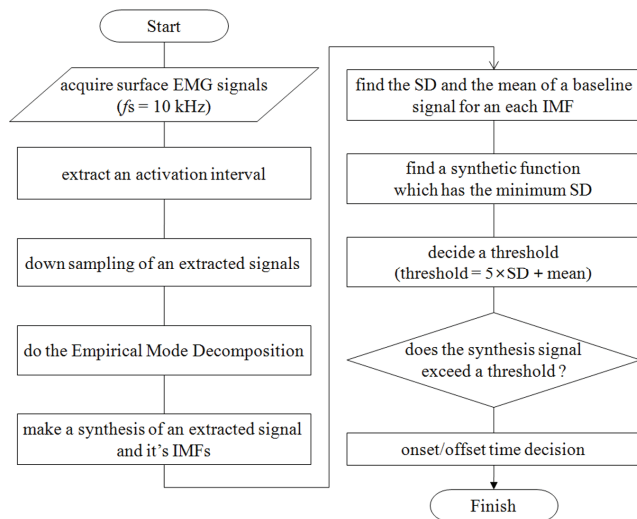


Fig. 1. A flowchart of the proposed method.

subjects are 31 persons with no abnormalities in their arms or contraction muscles. Their mean age is 26.5 years old.

Listing steps below show processes to detect the onset time. Because the early IMFs contain high frequency components relatively, it is needed to synthesize relative low frequency components which represents contraction-relaxation trend of the sEMG as like in the step 1.

Step 0: do the EMD method; find each IMF.

Step 1: make synthetic functions, s_i .

$$s_i = X - \sum_{k=1}^i IMF_k$$

X is single activation interval signal.

Step 2: find the SD and mean values in baseline stage – early 2.5 seconds, non-firing stage.

Step 3: find a synthetic function which has the minimum SD.

Step 4: decide a threshold.

$$\text{threshold} = 5 \times SD + \text{mean}.$$

Step 5: compare the threshold and the signal to detect onset time.

Steps from 0 to 5 are only concerning about the onset time detection. For the offset time detection, you may select baseline stage and find some values after firing (muscle contraction).

TABLE I
ERRORS OF ONSET/OFFSET TIME FOR 31 SUBJECTS, AMONG 3 METHODS.

	EMD		Di Fabio's		IP	
	onset	offset	onset	offset	onset	offset
error mean (ms)	123.3	150.2	197.5	202.4	181.7	229.0
error SD (ms)	88.7	119.5	400.1	259.0	110.1	133.1

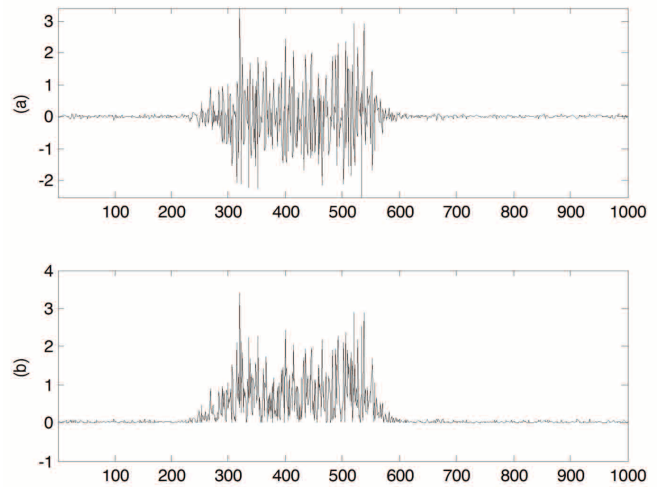


Fig. 2. One of sEMG signal recorded on the biceps brachii muscle. (a) A single activation interval of sEMG signal (10 seconds. A sampling frequency is 100 Hz, down sampled), (b) a rectified signal to be evaluated.

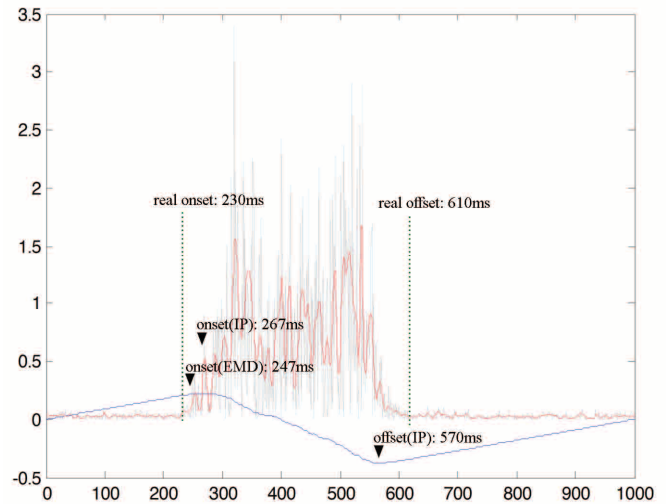


Fig. 3. Detection results of the onset time (at 3rd IMF). Gray line represents a single activation sEMG signal and red line represents the third IMF. Blue line represents a result of integrated profile (IP) method.

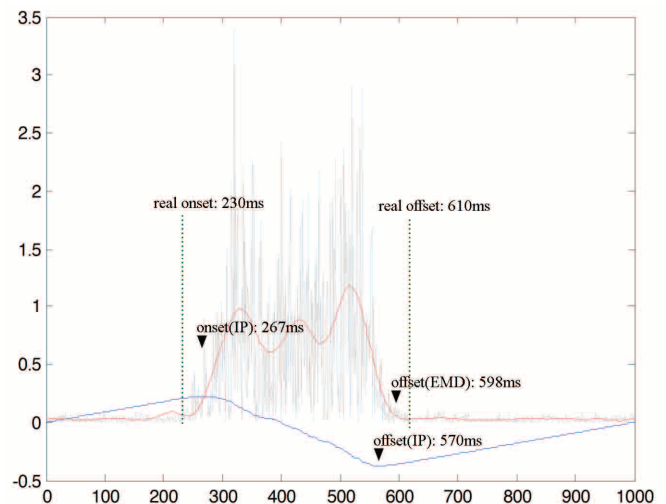


Fig. 4. Detection results of the offset time (at 7th IMF). Gray line represents a single activation sEMG signal and red line represents the seventh IMF. Blue line represents a result of integrated profile (IP) method.

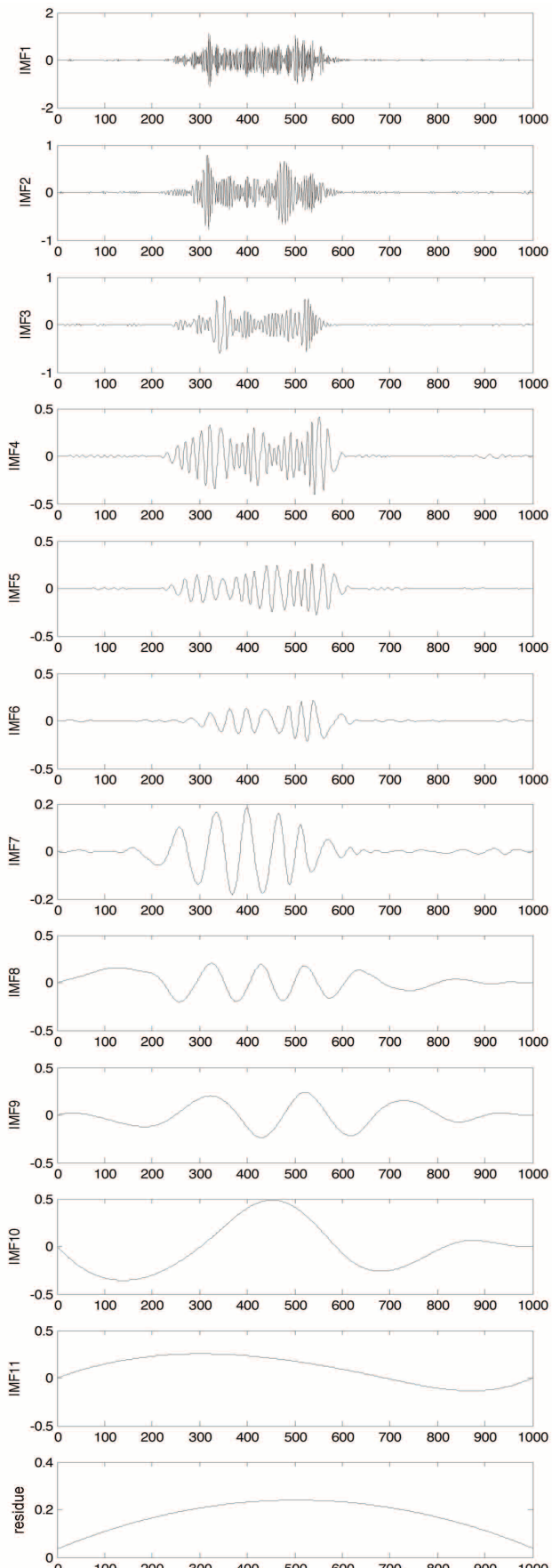


Fig. 5. IMFs of the sEMG signal in Fig.2 by empirical mode decomposition method.

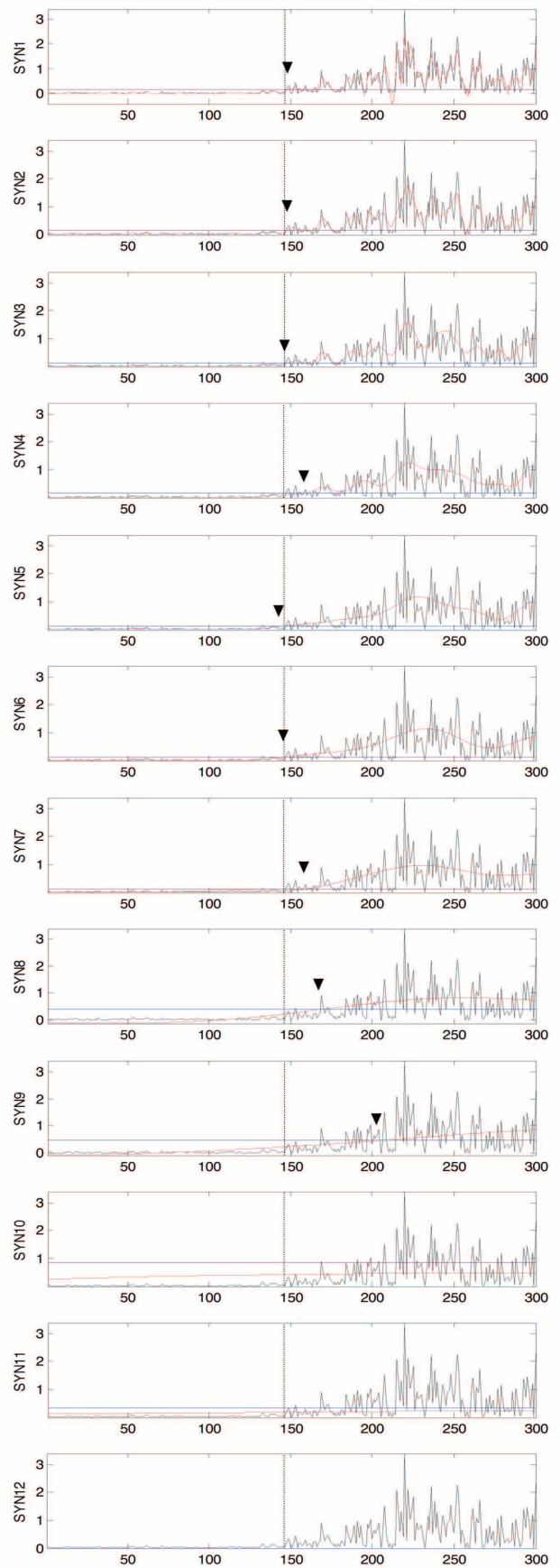


Fig. 6. The single activation signal (black), the synthetic functions (red) and their threshold (blue). The vertical dotted line denotes real onset time, and the black triangle denotes detected onset time.

In step 4, the multiplying factor value, five, is determined empirically. However it has to be determined considering the sampling frequency and the SNR. In general, more complicated signal needs bigger multiplying factor value.

III. RESULT AND DISCUSSION

The EMD method has the best match-up results for physical therapists. Table 1 shows the results of the onset and the offset errors in 31 subjects. Because of the iterative processing, the total computing time is quite long and varies from characteristics of sEMG signals. However, the EMD method is always used for off-line processing, the real-time property of the algorithm is unnecessary.

The IP method is also a strong tool for surface EMG signals. In this case, the mean value of errors is 181.7ms, and the SD value of errors is 229.0ms. The IP method is very fast to detect onset and offset times, but the IP method is not good at signals sampled by relatively high frequency. Figure 3 and 4 represent this kind of results.

Figure 5 shows 11 IMFs and one residue for the sEMG signal in Fig.2 by the EMD method. According to more iterative processes, the IMFs become to be a low-frequency waveform. We can make original EMG signals by adding all signals in figure 5. In figure 6, there are the synthesized functions corresponding to figure 5 of early 300 samples. In all synthesized signals, the detection results display in order (red lines). In this case, the third IMF is selected because it has the minimum SD in baseline signal (early 2.5 seconds).

There are some limitations in the proposed method. First of all, the EMD performance depends on some interpolation algorithm (in this case, we use the cubic spline) to generate IMFs. Secondly, it is not real-time detection technique. And finally, according to the empirical manner, there are no theoretical decomposing criteria to be explained.

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