34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Empirical Mode Decomposition as a Tool to Remove the Function Electrical Stimulation Artifact from Surface Electromyograms: Preliminary Investigation

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Abstract— **Rectification of surface EMGs during electrical stimulations (ES) is still a problem to be solved. The broad band frequency components of ES artifact overlap with the EMG spectrum, make this task challenging. In this study, we investigate the potential use of empirical mode decomposition (EMD) method to remove the stimulus artifact from surface EMGs collected during such applications. We hypothesize that the EMD algorithm provides a suitable platform for decomposing the EMG signal into physically meaningful intrinsic modes which can be used to isolate ES artifact. Basic EMD is tested on two signals – ES induced EMG and EMG of voluntary contractions added with simulated ES signal. The algorithm isolates the EMG from ES artifact with considerable success. Further, the EMD method along with the energy operator -TKEO gives even better representation of the EMG signal. However, some high frequency data was lost during reconstruction process. Hence, there is further need to investigate the relationship between the EMD parameters and stimulus artifact properties so that the algorithm can be optimized to reconstruct pure artifact free EMG signal with minimum lost of data.**

I. Introduction

Functional Electrical Stimulation (FES), operates on basic principle that the application of electrical current to a nerve can elicit the action potentials in neurons that are missing in paralyzed muscle [1]. Chronic application of electrical stimulation with varying frequencies and pulse widths has been used for many clinical and research interventions to improve tissue health or voluntary function by inducing physiological changes that potentially remain beyond the stimulation period [2]. The neuromuscular or neurophysiological effects of the ES have often been assessed through the collection of surface electromyography (sEMG), however the collection of EMG during the ES has been difficult to achieve [3, 4]. The most difficult challenge in the analyzing the EMG signal collected from electrically stimulated contractions is the presence of stimulus artifact. The stimulus artifact is a broad band signal with stimulus frequency harmonics and high amplitude and it completely engulfs the EMG. Removing the stimulus artifact is a signal processing challenge where the power spectrums of both the ES stimulus and EMG signal overlap. The standard frequency selective methods cannot be used as the filtered EMG will be distorted [5].

Historically, researchers have modified different hardware [6-8] and software [3, 5] approaches to elicit the EMG signal albeit each approach has limitations. Modifications involving hardware have included suppressing the stimulus artifact 'online' during signal acquisition utilizing a sample-and-hold technique [7]. For these techniques to be effective, the M-wave and the artifact spike should not overlap in time. A second approach developed by Heffer and Fallon, is to remove the artifact by replacing the sample points at each stimulus artifact event with values interpolated along a straight line, computed from neighboring sample points [5]. This technique requires an identifiable artifact event and the artifact duration must remain less than both the inter-stimulus interval and the time course of the action potential [5].

Considering the constraints or selective advantages of present techniques for artifact reduction in FES based experiments, there is a definite need for a robust algorithm, to clearly separate out the stimulus signal from the sEMG, without the need for prior information about the stimulus. Huang et al. have introduced a novel approach for analyzing non-stationary and non-linear data called as Empirical Mode Decomposition (EMD) [9]. This algorithm decomposes the signal based on the direct extraction of the energy associated with various intrinsic time scales [9], providing the opportunity to dissect non-stationary signal such as EMG to thoroughly understand the underlying phenomenon. The primary purpose of this paper is to determine the utility of basic EMD, for the removal ES artifact from the EMG signal. The EMG will be collected from one able bodied individual.

II. Methods

A. Data Collection

All data was collected from a 32 year old, healthy able bodied male, with no current or past history of any neuromuscular injury or disease. Prior to study participation a consent form approved by the Kessler Foundation's Institutional Review Board was signed.

The research participant was tested in a supine position with a bolster (6' diameter) placed under the knee of the leg being tested. The non tested knee was extended and the tested knee was flexed, with the shank 30 degrees from the right horizontal. Surface EMG (MA-300, Motion Lab Systems, Inc., LA.) data were collected for the right rectus femoris

This work was supported by Craig H Neilson Foundation grant (191152), New Jersey Commission on Spinal Cord Research grant (07-3063-SCR-E-0) and National Institute on Disability and Rehabilitation Research (NIDRR) grant for Advanced Rehabilitation Research and Training Center (ARRTC) on Neuromusculoskeletal Rehabilitation Post-Doctoral Training (143298).

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(RRF) during ES. ES was delivered by EMPi 300PV FES unit (Empi Inc., St. Paul, MN) through symmetrical biphasic pulses of 300 µs at 35 Hz applied across a 1000 ohm load. During testing the ES electrodes were placed at the medial-distal ends of RRF, where the subject achieved maximum contractions. An EMG electrode (E1) used to collect RRF muscle activation was placed midpoint between the two ES electrodes.

B. Data Processing

Basic Empirical Mode Decomposition (EMD)

The process used to decompose a signal $\mathrm{x}(\mathrm{t})$ into Intrinsic Mode Functions (IMFs) and a residual is called *Sifting* [9]. The steps involved in this decomposition are shown below:

1. The local maxima and minima are identified.
2. The local maxima are connected by an envelope obtained by fitting cubic spline. The process is repeated for local minima.
3. The mean of upper envelope and lower envelope, m_1 gives the first component which is then subtracted from $\mathrm{x}(\mathrm{t})$ to give h_1
4. Next, check if h_1 contains any riding waves and asymmetry. If yes, consider h_1 as a new data to get h_{11} using step 1 to 3.
5. Repeat this sifting process until h_{1k} is an IMF,

$$h_{1(k-1)} - m_{1k} = h_{1k} = c_1 \quad (1)$$

6. Separate c_1 from the original signal and repeat the process on residual till no further IMFs can be retrieved from the signal and we are left with the last residual r_n. Hence,

$$x(t) = \sum_{i=1}^{n} c_i + \mathrm{r}_\mathrm{n} \quad (2)$$

Excessive application of the sifting process can result into meaningless IMFs. Hence, the limitation on the standard deviation calculated from two consecutives sifting processes is used as a stopping criterion for sifting [9]. For our data, if the value of this standard deviation was greater than 0.1, the sifting process was terminated [9]. Thus the sifting process allows the signal $\mathrm{x}(\mathrm{t})$ to be decomposed into n IMFs with final residual r_n.

Teager-Kaiser energy operator (TKEO)

To further analyze the signal we applied the Teager-Kaiser energy operator (TKEO), introduced by [17]. The equation for determining the energy (E) of a discrete oscillating signal, x_n is given as,

$$E(x_n) = {x_n}^2 - x_{n+1}.x_{n-1} \quad (3)$$

The method simultaneously considers the amplitude and the instantaneous frequency of the surface EMG signal. It has shown that the TKEO amplifies the energy of the action potential spikes thus differentiates between the relaxed and contracted muscle [17]. The output signal of EMD is basically the EMG signal with residual ES artifact. These residual ES has the constant amplitude and the frequency (test signal 2) which can be negated by TKEO. Hence, this method complements the EMD algorithm, removes the baseline noise and improves the visual EMG onset detection accuracy.

III. Results

Signal 1 will involve the EMG of voluntary muscle contractions during ES. Test Signal 2 will be generated by adding voluntary muscle contraction collected in the absence of ES to the simulated ES signal. This will allow us to directly compare the filtered EMG signal with the original artifact free EMG signal.

Test Signal 1: EMG during ES induced contractions

The data collected from the electrode placed on right rectus femoris (RF) during constant amplitude electrical stimulations with test subject being asked to produce voluntary muscle contractions in supine position, is used as a test signal (Fig. 1). The data collection started with incrementing the ES until the full extension occurs. The subject is asked to produce a voluntary contraction 3s after the extension and asked to hold it for next 3s. The ES are then linearly reduced. The data is first band pass filtered with an FIR filter ($f_{cutoff} = [20{,}400]$ Hz) before the algorithm is applied. The basic EMD algorithm decomposed the test signal into 13 intrinsic mode functions (IMFs) as shown in Fig. 2. As mentioned in almost all of the EMD literature, the addition of all these modes and the residual will yield the original signal with minimum error.

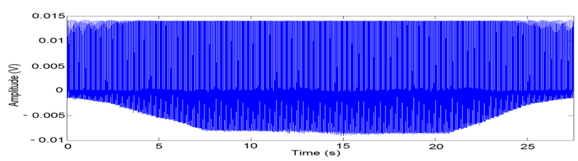

Fig. 1: The test signal – sEMG from right RF during FES

Hence, the idea is to decompose the signal into multiple modes and add those modes that are not affected by the stimulus artifact.

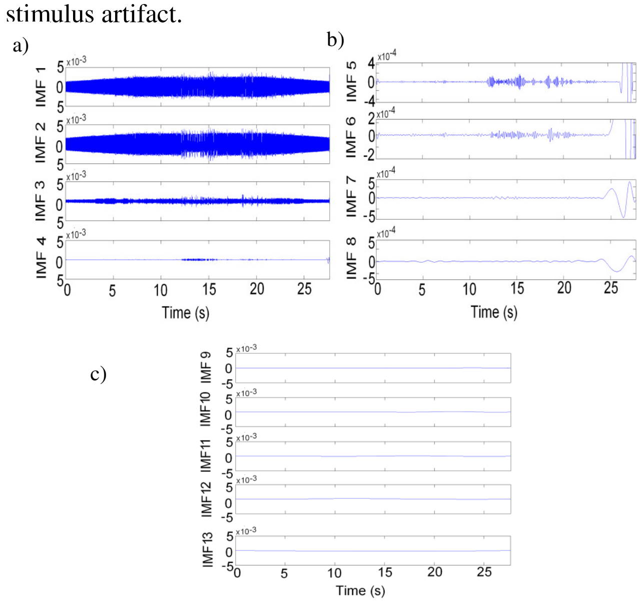

Fig. 2: The decomposition performed using basic EMD method to give (a) IMFs 1 to 4, (b) IMFs 5 to 8 and (c) IMFs 9-13

By visual inspection of the data (Fig. 2), the stimulus artifact is dominating the first three modes. IMF 4 to 6 appear as smoothed versions of the EMG signal (of different degrees) buried under the stimulus artifact. From IMF 4 onwards, each mode represents various bands of frequencies (high to low order) that constitute the EMG signal. As IMF 1 to 3 were the artifact affected modes, IMF 4 to IMF 13 are added to produce the EMG signal, shown in Fig. 3a.

a)
b)

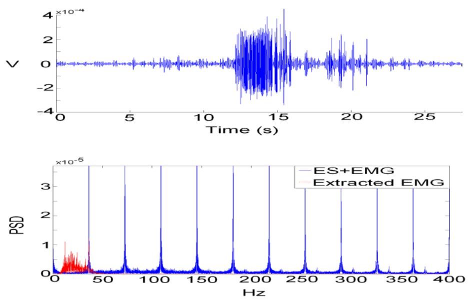

Fig. 3: (a) The reconstructed EMG using EMD algorithm and (b) its Fourier transform

As seen in Fig. 3a, the EMD algorithm was able to reconstruct the EMG signal with expected burst of ES induced contractions. The reconstructed EMG appears to be smoothed version of the original EMG signal. Although the algorithm was able to extract the two bursts of voluntary contractions, the higher frequency components present in the data were lost when IMFs 1 -3 were discarded from the data (Fig. 2b). As mentioned in EMD literature, EMD algorithm acts as a didactic filter and extracts the modes of frequencies from high to low order [19]. Hence IMF 1 and IMF 2 contain not only the stimulus harmonics but also high frequency components of the EMG data which were lost in the process of reconstruction. This suggests that the basic EMD although extracts some part of EMG buried under ES signal, it requires further conditioning of the signal to get the accurate output.

Test Signal 2: Voluntary EMG added with the simulated electrical stimulation signal

A train of pulses was generated using the command `pulstran(t,d,'gauspuls',fp,BW)` in Matlab. The parameters t, d, f_p and BW were selected so that the generated stimulus signal will match its experimental counterpart and have the same specifications such as sampling frequency, pulse width, stimulus frequency etc.

The generated stimulus signal (Fig. 4a) and the EMG signal collected during voluntary muscle contractions (Fig. 4b) were added to produce the test signal shown in Fig. 4c.

Basic EMD algorithm successfully extracted the burst of voluntary contraction from the overlaid simulated stimulus artifact. Further conditioning of this signal using TKEO considerably improves the quality of the signal by removing the baseline noise as seen in Fig. 5b. However, comparing the extracted EMG with the original (Fig. 4b), the high frequency data (75-300 Hz) is still lost (see Fig. 5c).

This indicates that basic EMD is limited as we cannot fully isolate the pure EMG data from the discarded IMFs 1-2 for both the test signals.

a)
b)
c)

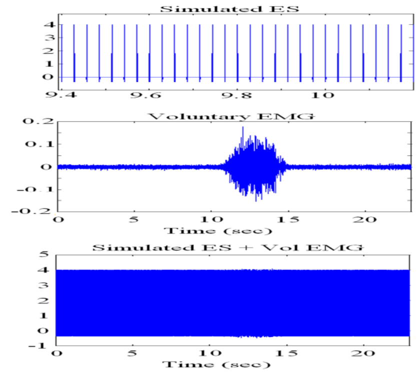

Fig. 4: (a) The simulated ES signal, (b) EMG collected during voluntary contraction and (c) the test signal generated by adding a and b

a)
b)
c)

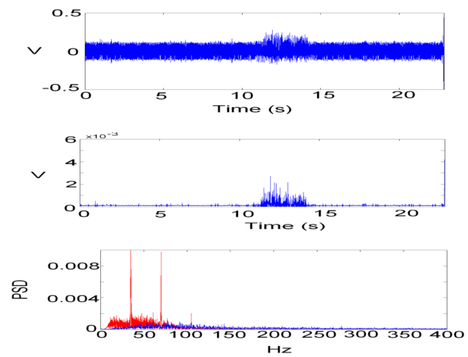

Fig. 5: (a) The extracted EMG signal using basic EMD, (b) conditioned filtered signal using TKEO (c) the FFT comparison of the original voluntary EMG signal (Fig. 7b) (blue) and the extracted EMG signal (red)

IV. Discussion

Extraction of surface EMGs during ES is still a problem to be solved. In this study, the potential use of EMD methods to remove the stimulus artifact from surface EMGs collected ES was investigated. As previously mentioned, O'Keeffe et al developed a two stage peak-detection algorithm for isolation of EMG from stimulus artifact however the method is only effective when the M-wave and the artifact spike do not overlap [3]. By comparison, the EMD methods (basic EMD and DI-EMD) outlined in this paper can distinguish the different modes that constitute the EMG signal at any instance of time using method of sifting, thus the EMD methods can provide a more optimal platform for extraction of M-wave from stimulus spikes. Heffer and Fallon removed the stimulus artifact by linear interpolation using neighboring sample points to replace the stimulus artifact [5]. Their technique is dependent on identification on the artifact event and the artifact duration must remain less than both the inter-stimulus interval and the time course of the action potential [5]. By comparison, the EMD based decompositions are simple to perform and do not need prior knowledge about signal properties such as artifact durations or instances for extracting the EMG as EMD based methods are completely driven by the data itself.

Another advantage of using the EMD methods is the lack of delay in the filtered signal and the EMG bursts are detected at the exact time of activation. The algorithms, while having no complicated filters perform point-by-point calculations, which make the methods very accurate in identifying the time instances of certain events in time-frequency representation as well.

From a physiological viewpoint, the EMD algorithms preserve some of the stochastic nature of the EMG signal in each mode, thus preserving the EMG physical significance whereas the more traditional decompositions performed using a FFT or a wavelet, the signal is broken down in waves (sine for FFT) that have little to do with the physiological processes of muscle contraction. Hence, instead of trying to distinguish between the artifact and EMG frequencies and then filtering them, EMD algorithms separate the signal into the artifact and EMG components in a way that preserves the intrinsic properties of each.

Further, when we applied TKEO algorithm, the resultant cleaner signal allowed for identification of burst durations due the very effective TKEO onset detection mechanism. Considering the intensity of the stimulus artifact, the rectified EMG obtained after TKEO is far better a representation of the physiological events occurring during the trial. If one is solely interested in the qualitative analysis of EMGs such as detection of EMG bursts at specific instances of time during any FES application, the basic EMD with TKEO, both serves as useful tool for signal analysis.

For this case study we investigated data for one able bodied individual as a first step towards proof of concept of our method. Future work needs to expand our: i) sample size of able bodied individuals and ii) analyses to include individuals with paralysis. The question still lingering is - can we trust the reconstructed signal as we are still losing some of the higher harmonics using basic EMD? Working with the EMG data collected from a stimulated paralyzed muscle we do not want to lose any small activity in the signal because that activity might be the only activity present. We also don't want to identify any false activity (stimulus harmonics) as a muscle response to the stimulus. In the process of filtering EMG signal, we discard first two IMFs for basic EMD. Ideally, we would like to have only stimulus artifact to be present in the first two IMFs and pure EMG data in the remaining IMFs. Hence, it will be interesting to further investigate the relationship between the algorithm parameters (e.g. order of spline fitting, number of sifting iterations) and the extracted IMF characteristics.

V. Conclusion and Future Work

We hypothesized that the EMD provides a suitable platform for isolating the non-stationary EMG signal from ES artifact by decomposing the signal into physically meaningful IMFs. The EMD method along with TKEO gives much better representation of the EMG signal. The data driven nature of these algorithm, accuracy of the onset detection, no system delays make these methods extremely suitable for EMG analysis in FES applications where even a simple visual assessment of collected EMG is difficult. However, there is further need to investigate the relationship between the EMD parameters and IMF properties potentially implementing a more automated approach for identifying the IMF's components. Also, different variations of EMD such as Doubly-Iterative (DI) EMD which provides flexibility with selecting the sifting parameters could also be tested in conjunction with more advanced EMD algorithms such as Ensemble EMD that can overcome mode mixing problem introduced by the conventional EMD algorithm.

Acknowledgment

Authors would like to thank Megan Damcott, Jerome Andre, Fend Wei, Arvind Ramanujam and Erica Garbanini for carrying out the data collection for this project.

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