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Abstract— **An adaptive method for reliable and fast detection of muscle activity from surface electromyographic (sEMG) signals is introduced. The aim of this research was to minimize the delay of the onset and termination detection, while still retaining the reliability and simplicity of the detection algorithm. The proposed algorithm is based on a double-threshold detector. The algorithm applies the same principles as a constant false alarm rate (CFAR) processor that is often used to distinguish events from noisy environments with dynamic noise characteristics. The algorithm was tested with different noise conditions and frequencies. For each condition, a set of 1000 computer-simulated EMG signals were processed multiple times with different processing parameters in order to find the optimal settings for reliable muscle activity detection. The results for the detection delays were comparable to previously published results, and for low-noise conditions the detection worked without errors. The performance of the algorithm was verified using real sEMG signals. Performance in termination detection that has often been neglected in prior studies, is also reported. The results show that the method could be applied in the targeted real-time application: facial pacing.**

Keywords— **double threshold detector, electromyography, facial pacing**

I. INTRODUCTION

The analysis of electromyographic signals and especially the detection of the onset and termination points of muscle activity is important in biomedical applications. One particular application field which benefits from fast and reliable muscle activity detection, is prosthetic technology that uses electromyography (EMG) to analyze the behavior of the subject for producing control signals. Facial pacing is an application that applies real-time measurement and functional electrical stimulation for reanimating unilateral facial paralysis. In order to pace natural-looking, symmetrical facial expressions, the delay of the muscle activation on the paralyzed side compared to the healthy has to be low. In a study by Kim et al., facial movements (excluding eye blinks) were perceived as synchronous by the majority of a test group, when the delay was less than 33 ms [1].

Several different approaches with varying complexity have been developed for the detection of muscle activations from surface electromyographic (sEMG) signals, but a gold standard for the task does not currently exist. A processing algorithm which detects discontinuities in the wavelet domain has produced excellent results for both onset and termination detection [2]. Other methods for the detection include for example a Teager-Kaiser operator [3], and a sequential gaussian mixture model in an EMG learning framework [4]. Singular spectrum analysis (SSA) is said to be especially suitable for neuroprosthetic applications because it can be directly applied to the raw signal in real-time, without any prior knowledge of the signal properties [5]. A double-threshold algorithm that works based on controllable values of detection probability, false-alarm probability, and time resolution parameters has also been used to detect sEMG onsets and terminations from raw myoelectric signals [6]. The onset and termination detection delays achieved with the aforementioned methods varied from less than ten to hundreds of milliseconds. The best results are gained with more complex methods, which can account for the variability and stochasticity of the EMG signals. On the other hand, the more complex the method, the harder it is to integrate as a part of prosthetic technology, and to maintain reasonably low processing time with often limited computational resources.

The goal of this study was to develop, optimize, and validate an EMG onset and termination detection algorithm that is suitable for facial pacing. The proposed algorithm is based on earlier work on double-threshold detectors. The termination detection delay and the accuracy of the detections that are important in real-time prosthetic applications, but often neglected in prior studies, are reported.

II. METHODS

A. The detection algorithm

The proposed detection algorithm can be considered to have mediocre complexity. The algorithm applies the same principles as a constant false alarm rate (CFAR) processor, which is an adaptive method that maintains a constant false detection rate for events in the observed signal, for example saccades in electro-oculographic (EOG) signals [7]. The CFAR processor can be applied to keep the probability for noise induced false detections constant, when the noise characteristics (e.g. gaussian distribution) of the observed signal are known. The adaptive threshold for an event is calculated by computing a statistical value, for example the average in cell-averaging CFAR, for the reference samples, and multiplying it with a sensitivity parameter. The samples adjacent to the test sample are excluded as guard samples and the ones next to these are the reference samples. In the case of detecting EMG activity, the properties of the CFAR processor are favourable due to the stochastic nature of the signal [8].

The operation of the proposed algorithm for detecting the onset and termination points of sEMG activity can be divided to four main functional components: initial high-pass filtering to remove baseline wandering, rectification of the filtered signal, determining if an onset has occurred, and determining if a termination has occurred. The initial filtering is done with a second order Butterworth high-pass filter. The signal is rectified by taking the square of each input sample. This also amplifies the high-amplitude values. In a conventional CFAR algorithm the signal is usually only rectified. Next, the number of reference samples (R) and guard samples (G), as well as a sensitivity parameter (S_o) are defined by the user for the onset detection with a cell-averaging CFAR. Only samples that precede the test sample are included as guard and reference samples. Based on the number of R and G, the algorithm creates a low-pass filtered reference signal (moving average of the rectified signal) for the onset detection, which when multiplied with the sensitivity parameter S_o, determines the adaptive CFAR threshold. The algorithm first compares the rectified signal to the CFAR threshold producing binary output with true values when the threshold is exceeded. An additional M-out-of-N sliding window detector is applied to the binary signal to make the final onset detection. If an onset is detected, the algorithm begins to search for the termination point by determining the threshold value for the termination detection by multiplying a user-selected sensitivity parameter (S_t) with the reference signal for the termination. In the case of termination detection, the reference signal is also a moving average of the rectified signal, but with a higher low-pass cut-off frequency than for the onset detection. When the sensitivity-corrected moving average is below the threshold as detected with another M-out-of-N detector, the algorithm marks it as a termination point. This type of termination detection is fast, but might fail if the noise level rises significantly during the muscle activation.

B. EMG simulation and processing of the simulated sEMG

An EMG signal can be considered as stochastic gaussian noise, and thus, it can be simulated easily [8]. More sophisticated and accurate methods for EMG simulation, involving motor unit action potential (MUAP) modelling, have been used in earlier studies [9], but for functionality testing of the algorithm, a simpler method was considered justifiable. The benefit of using simulated EMG, is that the actual onset and termination times are predetermined, and the detection delays can be evaluated precisely. In this project, EMG was simulated by using an algorithm to produce a gaussian noise signals with known signal-to-noise ratios (SNRs). The bandwidth of the simulated signals was restricted to 20–200 Hz.

A total of six sets of simulated EMG signals with two different SNRs (9.54 dB and 20.0 dB) and three different sampling frequencies (1024, 2048 and 10000 Hz) were processed to test the functionality and performance of the detection algorithm. These specific values for SNRs and sampling frequencies were chosen based on previous studies on the detection of surface EMG activity. Furthermore, the 10 kHz sampling frequency was included in order to help facilitate the method to an already-built facial pacing system. A set of signals with one thousand activations per each condition were generated and processed.

C. Measuring and processing of real sEMG signals

Real EMG data was gathered from 15 healthy participants (8 females, 7 males), whose age ranged between 26 and 57 years (40.7 $\pm$ 9.6). Principles outlined in the Declaration of Helsinki, were followed in the experimental study.

The experiment started with a one minute long resting task, after which the participants were asked to perform three facial movements: smiling, lip puckering and frowning. Each movement lasted 6 seconds and 10 repetitions of each movement were instructed to be performed in random order. The EMG signals from these movements in *zygomaticus major*, *orbicularis oris* and *corrugator supercilii* muscles were measured with pre-gelled and sintered Ag-AgCl electrodes. In addition, signal from the *orbicularis oculi* muscle was measured, to find out if eyeblinks could be detected. The measurement was bipolar and the electrodes were placed according to the guidelines of Fridlund and Cacioppo [10]. The used mea-

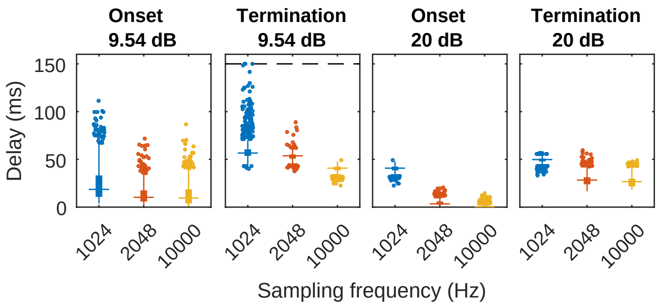

Figure 1: Onset and termination detection delays as boxplots for the 9.54 dB and 20.00 dB SNR simulated signals with different sampling frequencies.

surement device was NeXus-10 physiological monitoring device (Mind Media BV) with a sampling rate of 2048 Hz. The instructions were given via a screen and all movements were instructed to be done as naturally as possible.

III. Results and discussion

A. Results with simulated signals

The average delays of the onset and termination detection with each different signal sampling frequency, when using the simulated EMG signals with 9.54 dB SNR, are gathered in Table 1. The corresponding values for the 20.00 dB SNR signals can be seen in Table 2. Also, a boxplot of the detection delays at different frequencies is presented in Figure 1. The experimental iteration of optimum parameters for the detection algorithm in each condition was done by testing different values for the first sensitivity parameters (S_o and S_t) and for the number of samples (R_t) for the moving average filter of the termination detector. The other CFAR parameters were: $R = Fs/4$ and $G = Fs/10$, where Fs is the sampling frequency. Second threshold parameters for the M-out-of-N detectors were $M_o = 4$ and $N_o = 5$ for onset detection, and $M_t = 32$ and $N_t = 40$ for termination detection.

From Tables 1 and 2 it can be seen that the best results for the detection of the EMG signals and their onset and termination delays, was achieved with the highest sampling frequency. The SNR of the signal has a significant effect on the detection delays as well: the algorithm performs best, when the processed signal has a high SNR.

Table 1: Results for 9.54 dB SNR simulated EMG signals. The values represent optimized parameter values (S_o, S_t, R_t) with a certain sampling frequency (Fs), average onset detection delays with standard deviation (OD), average termination detection delays with standard deviation (TD), and detection-% (Det.-%)

Fs (Hz)	S_o	S_t	R_t	OD (ms)	TD (ms)	Det.-%
1024	8	1.5	26	23.7 ± 18.3	60.1 ± 13.2	99.3
2048	10	1.5	82	13.3 ± 10.3	53.0 ± 4.3	99.9
10000	20	1.5	400	13.0 ± 14.8	40.0 ± 4.3	99.9

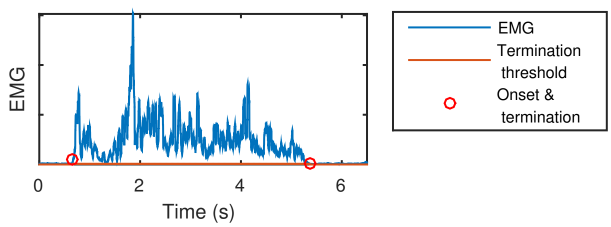

Figure 2: An EMG signal measured from the *corrugator supercilii* muscle with the termination threshold value, and detected onset and terminations points.

When comparing these results to some of the previously studied methods, it can be deduced that for a method with mediocre complexity, the algorithm performs extremely well. Comparative values for earlier proposed methods can be seen in Table 3. The termination times are often neglected in the results, even though they are important especially in neuroprosthetics.

In this study, only the 20.00 dB SNR results in satisfactory termination detection delay. Still, in regards of facial pacing applications, the results for the onset detection with the simulated signals are good: the onset delays are well below the 33 ms that was the limit of perception of synchronous movements in the study by Kim et al. [1]. In addition to the low latencies in detecting the activation points of EMG, the reliability of the detection algorithm is excellent. When processing high SNR signals, the method can be considered flawless in terms of detecting the EMG activity.

B. Results with real sEMG signals

An example of a real rectified EMG signal can be seen in Figure 2.

The number of measured signals for each movement was 150, but some of the real EMG signals had to be discarded, since even the visual inspection of the signal waveforms did not reveal any distinguishable change in the EMG amplitude. These cases might have been due to the failure of the participant to carry out the instructed movements or the fact that in

Table 2: Results for 20.00 dB SNR simulated EMG signals. For abbreviations, refer to Table 1

Fs (Hz)	S_o	S_t	R_t	OD (ms)	TD (ms)	Det.-%
1024	15	10	20	7.8 ± 3.8	49.0 ± 3.3	100.0
2048	20	2	10	4.7 ± 2.9	28.4 ± 6.5	100.0
10000	25	1.5	182	1.6 ± 1.9	26.8 ± 5.1	100.0

Table 3: Onset and termination detection delays (ODs and TDs) of earlier proposed methods. The values in the table represent the lowest detection delay achieved. The abbreviations: wavelet transform method (WTM), Teager-Kaiser (TK), sequential gaussian mixture modelling (SGMM), and double-threshold (DT)

Method	OD (ms)	TD (ms)
WTM [2]	6.5 ± 6.5	4.1 ± 5.3
TK [3]	$< 19 \pm < 3$	Not specified
SGMM [4]	$< 5 \pm < 3$	Not specified
DT [6]	$< 3 \pm < 2$	Not specified

Table 4: The results for the real EMG processing. Measured muscle, optimized parameters, false detection-% (FD-%), missed detection-% (MD-%), and detection-% (Det.-%).

Muscle	S_o	S_t	R_t	FD-%	MD-%	Det.-%
Zygomaticus	20	0.9	82	10.7	0.8	87.7
Corrugator	25	1.1	82	5.7	0.7	93.6
Oris	20	1.1	82	15.8	0.8	83.3

real life, the SNR of the signal is sometimes simply too low. The movements were chosen so that each of them activates a specific measured muscle: smiling activates *zygomaticus major*, lip puckering activates *orbicularis oris* and frowning activates *corrugator supercilii*. The sEMG signals from the *orbicularis oculi* muscle were so weak that the eyeblinks were not distinguishable in any of the signals. Different kind of electrode placement might have produced stronger signals, but usually eyeblink detection is not even done by utilizing EMG, but rather EOG signals. For *zygomaticus major* a total of 130 signal sequences were processed, and the corresponding quantities for *orbicularis oris* and *corrugator supercilii* were 120 and 140, respectively. The results are presented in Table 4. The fixed parameters were the same as for the simulated signals.

When comparing these results to previous studies, especially to the wavelet transform method (WTM) [2], the results are slightly worse, but still comparable. The WTM had a false detection rate of 3-7% and it did not miss any activations [2]. However, the signals, which were processed with the WTM were from leg muscles, so the signal SNR might have been significantly better than what was obtained from the facial muscles in our study.

The *corrugator supercilii* signals were the most probable signals to be processed without errors. Some of the signals, especially from the *zygomaticus* muscle, behaved oddly, when compared to the simulated signals. The ending of the muscle activation does not happen instantaneously, but gradually instead, which causes problems for the termination detection. When considering the target application, these problems in the termination detection must be taken into account. The termination point could for example be estimated based on the attenuation of the detected activity.

IV. Conclusion

A new, relatively simple method, suitable for embedded real-time EMG activation and termination detection was introduced. While the results with the simulated signals were promising, the processing of real EMG proved to be more challenging. The next logical step would be to test the method in an actual physical application. In this study it is shown that the proposed method produces satisfactory results and can be seen as a good option, when considering an application that needs real-time EMG detection, but which still has to retain its simplicity.

Conflict of Interest

The authors declare that they have no conflict of interest.

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