Muscle twitch responses for shaping the multi-pad electrode for functional electrical stimulation

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Abstract—In this paper we present a method for optimization of multi-pad electrode spatial selectivity during transcutaneous Functional Electrical Stimulation (FES) of hand. The presented method is based on measurement of individual muscle twitch responses during low frequency electrical stimulation via pads within multi-pad electrode. Twitch responses are recorded by Micro-Electro-Mechanical Systems (MEMS) accelerometers. The aim of this methodology is to substitute bulky sensors, torque sensors and goniometers, in multi-pad electrode optimization algorithm with smaller and lighter sensors; therefore making multi-pad stimulation suitable for daily use. Additionally we present method for minimizing number of MEMS accelerometers, which relies on characteristic waveforms of joint acceleration during wrist or fingers flexion/extension. These signals can be used to train Artificial Neural Network (ANN) to distinguish between different waveform classes and define correlation of each pad and activated muscle beneath. Results presented in this paper show high agreement of goniometers based classification and accelerometers based classification. As for classification with minimized number of sensors (one accelerometer) our ANN backed algorithm achieved high degree of accurate classification in intra-subject testing, but lower performance in inter-subject testing.

Index Terms—Multi-pad electrode, FES, artificial neural network, selectivity.

I. INTRODUCTION

Trends in Biomedical Engineering indicate widening possibilities in utilizing surface multi-pad electrodes in Functional Electrical Stimulation (FES) or Functional Electrical Therapy (FET) [1-3]. Many studies addressed electrical behavior of multi-pad stimulation by analyzing the current density under surface stimulation electrodes based on computer modeling, in vivo or in vitro experiments [4-6]. Sagi-Dolev et al. [8] analyzed the current density under surface stimulation electrodes with the aim to develop a method that will eliminate the problem of simultaneous activation of Flexor Carpi m. when Flexor Digitorum Superficialis m. and Flexor Digitorum Profundus m. are activated, which usually occurs during externally controlled grasping, and activation of afferent pathways (reflex reactions) when trying to control prehension. Based on previous findings, stimulation via multi-pad electrode emerged as step forward in FES technology. In order to incorporate multi-pad electrode in clinical praxis or home use, advanced automatic algorithms development was crucial. Fuji and colleagues [9] proposed the electrical stimulation system with automated multichannel surface electrodes, but there was no follow up of this work. Elsaify et al. suggested the method of using the muscle twitch response [10] for selecting of the optimal electrode which was created from several conventional single contact electrodes. The group from ETH, Zurich [4] presented the procedure for selective stimulation based on detailed model based analysis. This research provided evidence about the best size of the contact and distance between the contacts within the multi-pad electrode positioned on the skin. The group from University of Limerick, Ireland [11] demonstrated that the multi-pad electrode is leading to better selectivity during stimulation and presented the procedure how to select among the contact based on sensory information.

The process of selecting and classifying pads within multi-pad electrode based on muscle activation during stimulation (calibration protocol) is principal task for functional utilization of this FES technology. In order to make appropriate classification we need sensory feedback of joints movement during calibration protocol. The group from ETH, Zurich [12] developed finger and wrist torque measurement system for evaluation of grasp performance of multi channel stimulation. Multiple small pads and adjustable stimulation parameters, e.g. current amplitude and pulse duration, introduce many degrees of freedom in optimization of stimulation demanding automated algorithm for daily use of device based on multi-pad FES. Popović et al. [13] suggested automatic algorithm for optimization of multi-pad electrode, positioned on forearm, based on goniometers signals. As a follow up, our group extended proposed algorithm [14] with Artificial Neural Network (ANN) and accelerometers for optimization of stimulation.

These studies provided us insight in feasibility of employing bulky sensory system for applications in home and clinical environment. This proved to be main obstacle in daily use of optimization algorithms necessary for proper stimulation. In this paper we are concentrating in substitution of bulky feedback sensors with small and light Micro-Electro-Mechanical System (MEMS) accelerometers. In order to maximize efficiency of sensors we are proposing to use muscle twitch response, which is proportional to...
elicited muscle force when stimulating with individual current pulses [15]. This technique was presented for control of ankle joint in study by Elsaify et al. In our pilot study we compared visually noted wrist and finger twitch movement due to single pulse stimulation with signal obtained from the accelerometer positioned on the dorsal side of the hand. Based on the conducted measurements we evaluated feasibility of replacing bulky sensors with cheaper, smaller and lighter MEMS accelerometers, which are more suitable for daily use. As our intention was not to provide quantitative measure of finger/wrist movement, rather to find a simple but reliable method for multi-pad electrode calibration, we considered reducing number of MEMS sensors to only one sensor, and using signal waveform shape as supplementary information for decision making. The classification was performed using trained ANN. Positive results encouraged us to extend our research with two additional accelerometers placed on the middle and ring finger, in order to examine how different locations of the sensor influence ANN classification accuracy. In order to provide consistent observations instead of the visual inspection of twitch responses, and based on the straightforward dependency between muscle twitch response and muscle response to pulse train stimulation, we introduced additional protocol employing 30 Hz stimulation and goniometers recordings as benchmark and the neural network targets.

II. MATERIALS AND METHODS

A. Subjects

The experiments included 6 subjects with no known neurological disease history. All subjects signed informed consent approved by the local ethics committee.

B. Experimental procedure

Experimental procedure consisted of two protocols:

1) Twitch protocol – single current pulses were delivered 9 times in a row via each pad, with frequency of 2 Hz. All 16 pads were activated sequentially. Muscle twitch responses were measured with three-axial accelerometers (MMA7260Q, Freescale Semiconductor) positioned on the dorsal side of the hand and top of the middle finger and ring finger, as shown in Fig.1. Only one axis was used for the measurement. Sensitivity was set to ± 3g.

2) Continuous protocol – current pulse trains with frequency of 30 Hz and train duration of 2s were delivered via each pad sequentially. Pause between two subsequent trains was 1s. Joint angles were measured with Penny & Giles flexible goniometers (Biometrics, Gwent, U.K.) placed on the wrist, and over the middle and ring metacarpophalangeal (MCP) joints, as shown in Fig.1. The outputs of the goniometers were connected to joint angle display ADU301 produced by Biometrics, Gwent.

The signals were acquired using a PC computer via the DAQ 6212 by National Instruments, Austin, Texas, U.S.A. USB card at sampling rate of 1 kHz, and recorded by a custom made program in Matlab.

For the stimulation we used FES module, which produced monophasic, current controlled pulses. The pulse duration was 250µs and amplitude was set to the minimal value which produced visible movement in the wrist and fingers. We used oval 4x6 cm Pals Platinum electrode as an anode, and a custom made multi-pad electrode named INTEFES as a cathode. Electrode controller (PIC 18F4520) was programmed to set one of the pads within multi-pad electrode to active state in a predefined manner.

The subjects were seated comfortably in a chair, with their arms hanging relaxed next to the body. The experiment was repeated for each subject several times, and the INTEFES electrode was always removed and placed again in a different manner to include the variability of the motor point position assessment. Due to better clarity, only two trials per subject are presented in the results.

The tests were designed to measure the influence of the stimulation point on the twitch response in the hand, with a minimal number of sensors. The recordings from the twitch protocol were used to train the neural network to distinguish between different types of movement in hand: wrist flexion, finger flexion or none, and recordings from the continuous protocol were used as targets.

C. Data analysis

Two analyses were performed with recorded data. First, we compared muscle twitch amplitudes during Twitch protocol with angles achieved during Continuous protocol. In this analysis we derived information about presence/absence of joint flexion/extension using only signal amplitudes. Rule-based program classified pads based on muscle twitches and joint angles. Figure 2 shows signals from accelerometers during Twitch protocol for subject 6.

Muscle twitch amplitudes (see Figure 2) on different sites which produced visible movement in the wrist and fingers. Figure 1. Experimental setup.
classification by analyzing twitch amplitudes using all 3 accelerometers (Figure A). As shown in Figure 3, amplitudes of accelerometers signals and goniometers differs one from another. In order to get qualitative evaluation of this method we provided benchmarking performance relying on goniometers signals during Continuous protocol. In both methods we made classification of pads based solely on activated muscle not on strength of muscle contraction.

Fig. 2. Accelerometers signals measured on wrist (dorsal side of the hand), middle finger and ring finger during twitch protocol. Resulting joint movements are classified as wrist (W), middle finger (M), ring finger flexion (R) or no flexion (X) by the algorithm based on goniometers signals.

Fig. 3. Normalized twitch amplitudes and goniometers signals for subject 6.

After classification of pads we can illustrate their spatial distribution (Figure 4) and get insight of nerve structures underneath skin.

In order to minimize number of sensors needed for accurate calibration procedure (pad classification) we derived a method based on signal waveform shape recognition. Fig. 5 shows transition from one active pad to another measured with accelerometer positioned on dorsal side on the hand. First three muscle twitch waveforms are produced by wrist flexion and last three by finger flexion. It is noticeable that movement induced in wrist results in single sinusoidal mechanical wave as opposed to double belly wave if finger flexor is activated. We exploited this characteristic in order to automatically distinguish these two possible outcomes during forearm stimulation. One of the obstacles in this classification methodology is variability of waveform amplitudes, phases and characteristic features in subsequent intra-subject and particularly in inter-subject measurements. Because of this, we decided to employ generalizing ANN to overcome inconsistencies in measured waveforms.

We employed two signal conditioning and two neural networks for decision making. In first ANN method (raw method) recorded data were filtered with a moving average filter in 30 points to obtain smooth signal. Additionally, a DC value was removed and accelerometer signal was down sampled to 400 Hz.
ANN1: First 80 samples (200ms) after each stimulation pulse (trigger) were used as input to a neural network (Fig. 4-5). Using less than 80 samples (40, 20 or 10) decreased network performance, while using more samples didn’t produce any better results. This time window (200ms) permits extraction of induced muscle twitch out of voluntary movement. Perceptron neural network comprised 80 inputs (80 samples) and 3 outputs (wrist, middle finger or ring finger flexion). Data from first analysis (with all sensors included) regarding pads classification was used as target data during ANN training. The network was trained with one set of data from one subject and tested in all other data sets. Additionally, we tested the same network performance in case where inputs were previously differentiated in order to emphasize characteristic waveform slopes.

ANN2: In the second ANN method we concentrated on signal feature extraction. As in first ANN method, accelerometer signal was smoothed with a moving average filter in 30 points. Then, we obtained first time derivative of the signal and Fast Fourier Transform (FFT) in 200 points. Since components selected for classification are at low frequency we limited FFT amplitude spectrum to first 15 components. These components represent inputs to the ANN (15 inputs). ANN employed for this task was Feed-forward backpropagation network with one hidden layer comprising 5 neurons. All three layers had hyperbolic tangent sigmoid (tansig) transfer function. Targets during training and validation were classified pads from the analysis using goniometers signals.

III. RESULTS AND DISCUSSION

In our first analysis we demonstrated methodology for calibration of the multi-pad electrode for grasping. Results from the first analysis confirm our hypothesis that we can adapt calibration algorithm and replace sensory system used in previous studies [12-13]. Our rule based classification using accelerometers signals agree with classification using goniometers for more than 96 ± 2% pads.

As a step further, we introduced pads classification using waveform of an accelerometer signal, thus minimizing number of sensors. We tested two methods for data analysis coupled with appropriate networks. Both ANNs achieved 100% accuracy on trained data set. Trained ANN was then tested on all data sets, Table 1.

<table>
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<th>Subject</th>
<th>Data set</th>
<th>Accurate classification</th>
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<tr>
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As shown in Table 1, both ANN procedures achieved intra-subject classification exceeding 90% (93 ± 5 % and 95 ± 3%) which, when using 16 pad electrode, means that one pad is incorrectly classified. When we tried to classify signals obtained from other five subjects accuracy dropped to 81 ± 8 % (3 ± 1 pads incorrectly chosen) for raw data and 88 ± 4 % (2 ± 1 pads incorrectly chosen) for feature extracted data. This result shows a better performance and robustness of the ANN classification relaying on analysis in frequency domain. This finding is supported by our methodology where we discarded FFT phase spectrum. The phase shift in accelerometer signals significantly changes ANN input values (raw method) which induce systematic error.

IV. CONCLUSION

Presented method for fast optimization of multi-pad electrode relies on muscle twitch response to single stimulation impulse. For classification equivalent in results with goniometric algorithm we positioned accelerometers on the same joints but changed stimulation pattern. In this experiment we induced 9 twitches to each pad in order to test consistency of muscle twitch responses, but functional device will need only one pulse per pad. This property significantly shortens time needed to select pads within multi-pad electrode which activate desired nerve beneath. By using only one axis of one accelerometer we achieved high degree of accurate classification in intra-subject test. Inter-subject test produced not as good classification results, implicating importance of adapting ANN to every person to meet individual mechanical characteristics or using accelerometers positioned on all fingers and wrist.
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References


