Myoelectric signals and pattern recognition from implanted electrodes in two TMR subjects with an osseointegrated communication interface

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Abstract— **Permanent implantation of electrodes for prosthetic control is now possible using an osseointegrated implant as a long-term stable communication interface (e-OPRA). The number of myoelectric sites to host such electrodes can be increased by Targeted Muscle Reinnervation (TMR). Traditionally, patients need to wait several months before the TMR signals are strong enough to be recorded by electrodes placed over the skin. In this study, we report the evolution of the TMR myoelectric signals recorded from two subjects via implanted electrodes using e-OPRA, and monitored for up to 48 weeks after surgery. The signals were analyzed with regard to amplitude (signal-to-noise ratio), independence (cross-correlation) and myoelectric pattern recognition (classification accuracy). TMR signals appeared at the first follow-up, one month post-surgery, and developed around 20 dB by the last. Cross-correlation between signals decreased over time and converged to a few percentage points. Classification accuracies were over 97% by the last follow up. These preliminary results suggest that implanted electrodes via the e-OPRA interface allow for an earlier and more effective use of motor signals from TMR sites compared to conventional skin surface electrodes.**

I. Introduction

Promising developments are currently ongoing worldwide in the fields of neuroprosthetics and artificial limbs. A long-term stable connection of a robotic limb to the bone, nerves and muscles of a human being is now possible. In 2014, Ortiz-Catalan *et al.* demonstrated long-term bidirectional communication between an artificial limb and implanted neuromuscular electrodes by incorporating signal feedthrough mechanisms into an osseointegrated implant for bone-anchored limb prostheses [1]. This osseointegrated human-machine gateway was an enhancement of the bone-anchored OPRA implant system, referred to hereafter as e-OPRA. The e-OPRA technology is currently under clinical investigation in humans (NCT03178890), which provided the research framework for the study presented here.

Modern surgical techniques allow for redirecting a nerve, deprived from its original target muscle due to amputation, to a new target in order to access the original motor signals. This idea was proposed by Hoffer and Loeb in 1980 [2] as a way to potentially amplify neural signals via new target muscles. This concept was then brought to clinical reality in 2004 by Kuiken *et al.,* and named Targeted Muscle Reinnervation (TMR) [3]. TMR allowed a patient with bilateral shoulder articulation to control 3 Degrees-of-Freedom (DoF) of an arm prosthesis [3]. In 2009, TMR was more formally assessed with five patients [4], and since then used further in bionic reconstruction [5].

Intelligent signal processing and decoding algorithms can now utilize the electromyographic (EMG) signals recorded from the remaining muscles on the stump to infer the motor intention of the amputee, thus providing an intuitive control interface [6]–[8]. Myoelectric pattern recognition has outperformed conventional direct control in a randomized clinical trial in subjects with TMR [9]. However, a challenge in TMR subjects is the stable placement of several surface electrodes required to capture all the available myoelectric sites. In addition, patients need to wait several months before the innervation can produce signals strong enough to be detected with superficial electrodes. The aforementioned limitations can be overcome using implanted electrodes with the e-OPRA implant system.

In this study, we present the development of myoelectric signals (MES) in two amputee subjects who underwent TMR surgery and e-OPRA implantation. In addition, we applied myoelectric pattern recognition (MPR) to analyze the potential of this control modality in subjects with both TMR and e-OPRA.

II. Methods

Data was collected for up to 48 weeks from two subjects (hereafter referred to as A and B), who underwent TMR surgery and e-OPRA upgrade implantation in January 2017. The analysis was focused on the quality of the myoelectric

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signals from the implanted electrodes in terms of amplitude, independence, and accuracy of myoelectric pattern recognition. This study was approved by the Swedish regional ethical committee in Gothenburg.

A. TMR and e-OPRA

The TMR approach was to redirect the radial nerve into the lateral head of the triceps, and the ulnar nerve into the short head on the biceps, which would allow for intuitive myoelectric signals for hand open and close, respectively. Hereafter the two TMR channels will be referred to as TMR-radial and TMR-ulnar.

The subjects were previously implanted with the OPRA Implant System in 2014 and 2015. The enhancement to the e-OPRA consisted of the implantation of a series of signal feedthrough components and four bipolar electrodes on triceps and biceps muscles. One electrode was placed on each of the TMR-radial and TMR-ulnar sites, as well as on the naturally innervated heads of the triceps and biceps muscles. All muscular electrodes were epimysial except the TMR-ulnar in subject B, which was intramuscular. In addition, two four-contacts cuff electrodes were placed on the median and ulnar nerve of each subject.

B. Data collection

From January 2017 to February 2018, the subjects were invited to periodic follow-ups with an average periodicity of 7.3 weeks (SD=4.8 weeks), based on patient availability. During each follow-up, at least one recording session was performed on the epymisial electrodes to keep track of the state of the implanted interfaces. All the recordings were performed with the Artificial Limb Controller, an embedded system for controlling prosthetic devices designed for the e-OPRA implant users [10]. Data was sampled at 1000 Hz with 24-bit resolution. Embedded processing routines filtered the samples with high-pass and notch filters at 20 Hz and 50 Hz, respectively. Each recording was performed with BioPatRec [11], an open source, Matlab-based platform for research on myoelectric pattern recognition, which ran on a computer wirelessly connected to the Artificial Limb Controller. The recording protocol required the subject to sit in front of the computer in a relaxed position, and to follow the on-screen instructions. The recording sessions consisted in a sequence of four movements with three repetitions for each, alternating three seconds of contraction time with three seconds of rest time. The movements were: open hand, close hand, flex elbow and extend elbow. The subjects were asked to perform all movements with a consistent muscular effort of approximately 70% of maximum voluntary contraction.

C. Amplitude Analysis

The EMG signal-to-noise ratio (SNR) was used to quantify the quality of each MES independently. Similarly to previous work, a statistic ratio of signal and noise power was calculated from a recording session of three repetitions [12]. The 30% central portion of contraction and rest signals were extracted from each repetition for the same movement. The portions were then concatenated in two different arrays for MES and noise at rest, respectively. From these, RMS values were calculated with (1) to obtain the SNR.

$$SNR_{dB} = 10 * log_{10} \frac{{MES_{RMS}}^2}{{REST_{RMS}}^2} \qquad (1)$$

D. Independence Analysis

The MES data in the SNR calculations was also used for analyzing the independence between the channels. Similarly to previous studies [13]–[16], the cross-correlation function was used to determine the amount of common signal between channels within the same movement. Equation (2) was used to cross-correlate two signals, *x(t)* and *y(t)*.

$$R(\tau)_{xy} = \frac{1}{T}\int_0^T x(t)y(t+\tau)dt \qquad (2)$$

The function was then normalized with respect to the zero-phase shift values (or peaks) of the auto-correlations of *x(t)* and *y(t)*, and squared [14]. The ${R'_{xy}}^2$ function was considered as the relative common power between the two signals *x* and *y*. The channel expected to be the most prominent for a given movement was deemed as the reference channel for that movement. Thus, the reference channels were 1) TMR-radial for open hand, 2) TMR-ulnar for close hand, 3) biceps for flexion of the elbow, and 4) triceps for extension of the elbow.

E. Myoelectric Pattern Recognition

The machine learning tools from BioPatRec were used for myoelectric pattern recognition [11]. The Linear Discriminant Analysis (LDA) classifier was used in combination with four time domain features: absolute mean, waveform length, zero crossing and slope changes [11]. Features were calculated over 200 ms time windows with 50 ms increments, resulting in 121 time windows per movement. Time windows were assigned randomly to training and testing sets by 60% and 40% of the total feature vectors, respectively. The randomized sets were used to train the classifier in a One-vs-One topology [6]. This operation was repeated 10 times and the average accuracy between all movements for all iterations was taken as the result.

III. Results

The amplitude analysis, depicted in Figure 1, confirmed for both subjects, the development of the TMR-radial and TMR-ulnar. A few days after the surgery, the SNR values were near zero, meaning that mostly noise was recorded from those sources. After 4 weeks, the SNR of subject A's TMR-ulnar reached 8 dB, and surpassed 30 dB after week 19. Subject B's TMR-ulnar developed later, with non-negligible SNR values until week 7, after which its SNR settled to around 20 dB. For both subjects, the TMR-radial showed a delayed development process. Stable SNR values (between 10 and 15 dB) were found only after 15 weeks for subject B and 19 weeks for subject A. The signals on the remaining portions of triceps and biceps were similar across subjects and follow-ups (triceps ≈ 40 dB and biceps ≈ 25 dB).

The results of the crosstalk analysis are reported in Figure 4 and Table I. The percentage of common signal between the channels decreased over time (Figure 4) consistently with the development of the TMR signals. High peaks of

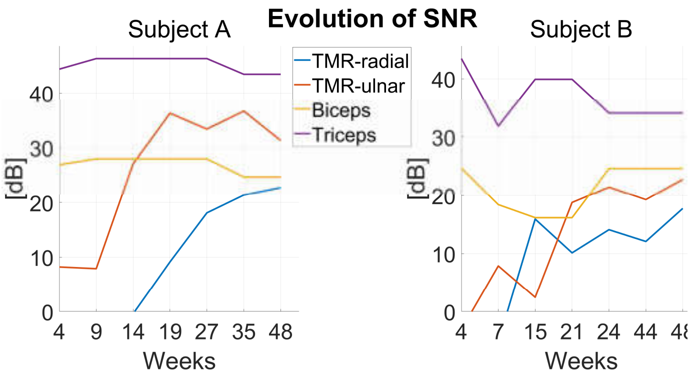

Figure 1: Evolution of SNR values.

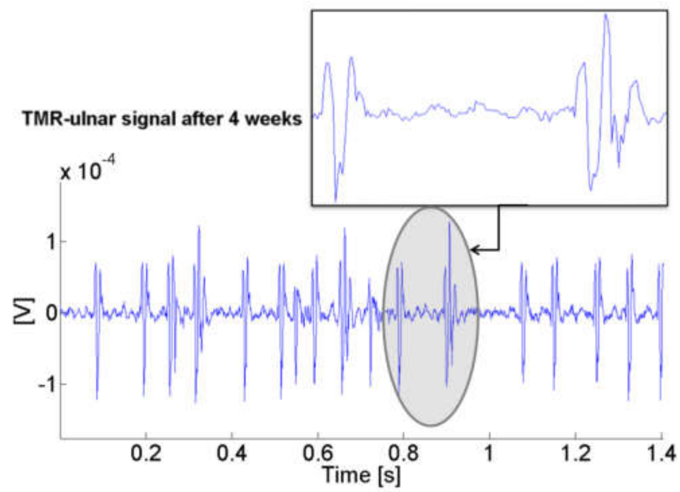

Figure 2: Myoelectric signal recorded from subject A at the first follow-up, 4 weeks after surgery.

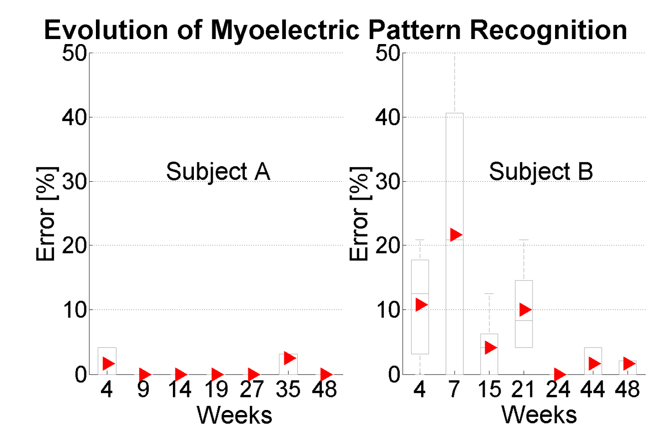

Figure 3: Evolution of Myoelectric Pattern Recognition. The boxplots represent the percentages of error for subject A (left) and B (right) over time. The triangular marker shows the mean error across all movements, and the horizontal line shows the median value.

correlation were found between the TMR-radial and the TMR-ulnar channels around week 9 for subject A and week 7 for subject B. Moreover, subject A had a relevant percentage of common signal between triceps and TMR-radial channels, but the values reduced over time. Values from last follow-up are reported in Table I.

The Myoelectric Pattern Recognition analysis results are plotted in Figure 3. For subject B, a consistent improvement was found over time. The initial mean error of 10.8% decreased to 1.7% at the last follow-up (week 48). For subject A, the error percentage was stable and never above 5%.

IV. Discussion and Conclusions

In January 2017, two transhumeral amputees underwent TMR surgery where electrode ware implanted in each of the targeted muscles. The myoelectric SNR confirmed a satisfactory development of reinnervation. At the last follow-up, the measured SNR values were above 10 dB. Overall, the TMR-radial needed more time to develop, requiring from 15 to 19 weeks for both subjects. This delay might be attributed to the difference in diameter (number of motor fibers) between the radial and ulnar nerves.

The amplitudes between the natively innervated triceps and biceps muscles showed a consistent difference. The SNR values from the triceps muscle were approximately 20 dB higher than the biceps muscle. The muscle size and potential misalignment between the poles of the epimysial electrodes could explain the discrepancy. Alternatively, the TMR surgery may have deprived the triceps of only a third of its original size, while it deprived half of the biceps. A more detailed analysis of the subjects' anatomy could help to further understand the discrepancies.

The signal independence analysis, via cross-correlation, revealed a low percentage of common signal between the reference channel of each movement and the others. High correlations were found between the TMR channels for both patients initially, but these reduced over time. This is possibly explained by the fact that the TMR channels were not properly developed at the time. At the first follow-ups (before week 15), the EMG activity from TMRs was a series of spaced single action potentials, still too distant in time to combine with each other (Figure 2). This phenomenon was not measured by the SNR as it averages the EMG segments. In addition, training was required for the subject to understand which phantom movement would produce the highest activation of the TMR signals. Nevertheless, the percentage of common signal between channels was reduced over time, particularly for subject B.

TABLE I

CROSSTALK ANALYSIS: PERCENTAGES OF COMMON SIGNAL BETWEEN CHANNELS FOR SUBJECT A (LEFT) AND SUBJECT B (RIGHT)

Movement / Channel	Open Hand	Close Hand	Flex Elbow	Extend Elbow
TMR-radial		0.9	0.6	2.1
TMR-ulnar	2.8		0.7	1.2
Biceps	2.9	1.0		4.6
Triceps	6.1	1.1	1.4	

Movement / Channel	Open Hand	Close Hand	Flex Elbow	Extend Elbow
TMR-radial		0.7	0.5	0.6
TMR-ulnar	0.8		0.8	0.6
Biceps	0.6	0.9		0.7
Triceps	1.2	2.0	0.7	

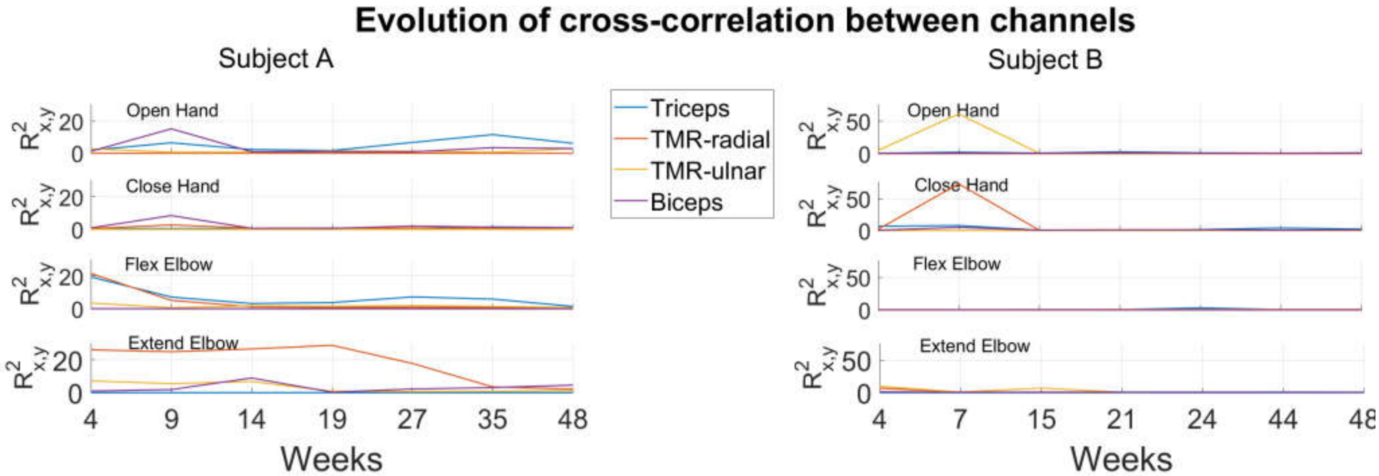

Figure 4: Evolution of the cross-correlation between myoelectric signals corresponding to different intended movements. Each plot corresponds to a movement (indicated by text in the graph) and shows the correlation of its reference channel with the others. The channel expected to be the most prominent for a particular movement was deemed as the reference channel for that movement. The reference channels were 1) TMR-radial for open hand, 2) TMR-ulnar for close hand, 3) biceps for flexion of the elbow, and 4) triceps for extension of the elbow.

The Myoelectric Pattern Recognition tests confirmed that this approach could result in better controllability of the prosthesis, similarly to what found in previous studies. The averaged accuracies remained effectively unchanged over the weeks for subject A. Oppositely, the LDA algorithm found more difficulties in analyzing subject B's data. It can be argued that this was related to the training period required by the subject to master the activation of the TMR signals, especially for week 7. However, the error converged to a few percentage points by the last follow-up. Surprisingly, the error was higher in the subject with less cross-correlation. It is important to note that these tests only represent offline accuracy, and are not conclusive for real-time functionality. Therefore, a complementary investigation on real-time myoelectric pattern recognition will be conducted in future work with focus on clinical translation. This study represents one of the first reports on TMR development with intramuscular electrodes in humans.

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