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Decoding Individuated Finger Flexions with Implantable MyoElectric Sensors

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Abstract

We trained a rhesus monkey to perform randomly cued, individuated finger flexions of the thumb, index, and middle finger. Nine Implantable MyoElectric Sensors (IMES) were then surgically implanted into the finger muscles of the monkey's forearm, without any observable adverse chronic effects. Using an inductive link, we wirelessly recorded EMG from the IMES as the monkey performed a finger flexion task. A principal components analysis (PCA) based algorithm was used to decode which finger switch was pressed based on the recorded EMG. This algorithm correctly decoded which finger was moved 89% of the time. These results demonstrate that IMES offer a safe and highly promising approach for providing intuitive, dexterous control of artificial limbs and hands after amputation.

I. Introduction

A major challenge facing the field of neural prosthetics is the issue of obtaining stable access to a sufficient number of neural signals to allow users intuitive control of their prosthesis. Neuroprosthetic devices typically gain access to neural signals through a percutaneous connector. This percutaneous connector is susceptible to infection and increases the risk of the prosthesis user suffering additional limb trauma, e.g. dislodging the connector and/or the implanted neural recording device thus damaging the nerve and the area surrounding the implant. Electromyographically (EMG) controlled prostheses using surface EMG electrodes avoid problems with infection and connector failure; however, it can be difficult to obtain more than three or four independent control signals on a residual limb using surface EMG electrodes [1], [2]. Implantable EMG sensors may be able to obtain a higher number of independent control signals from a residual limb than would surface electrodes and could avoid the risks associated with percutaneous implants. We examined whether wireless Implantable MyoElectric Sensors (IMES) could provide a stable long-term interface with high channel independence for EMG signals from the finger, wrist, and thumb flexors and extensors in a macaque monkey.

II. Methods

The Behavioral Task

A male monkey (*Macaca mulatta*) was trained to perform randomly cued flexions of the thumb, index finger, and middle finger using a manipulandum which uses microswitches to monitor finger flexions and extensions (Fig. 1) [3]. The behavioral finger task was programmed using LabVIEW (National Instruments) and ran on a real-time embedded computer. A computer screen placed in front of the monkey was used to visually cue the desired finger flexion. The first state in the behavioral task requires that the monkey relax all his fingers so that none of the finger switches are pressed (Fig. 2). The monkey then waited for the finger flexion cue for a randomized time between 1000-3000 ms. At the end of this wait period the monkey received a visual cue indicating which finger it should flex. The monkey then had 1000 ms in which to flex the cued finger and depress the associated microswitch. The monkey was required to keep the microswitch pressed for a 500 ms hold time. If the monkey flexed the correct finger and did not violate the timing constraints, it received a juice reward.

IMES

Each IMES was approximately 1 mm in diameter and 15 mm long, with active electrodes on each end [4]–[6]. Inductive coupling was used to power the IMES and transmit the EMG data [7]. We surgically implanted nine IMES into different finger and wrist flexion and extension muscles of the monkey's right forearm (Fig. 3). We attempted to implant each IMES into a muscle whose function in flexing or extending the thumb, wrist, or fingers was independent from the muscles in which other IMES were implanted (see Table I). Due to the constraints of the size of the receiving/transmitting coil, the IMES in the thenar eminence, near the thumb of the monkey's hand, lies too far outside the magnetic field to transmit EMG data. Therefore, the data we analyzed in this paper are from the other 8 IMES. These eight IMES have been successfully transmitting EMG data since July 2007 (Fig. 4). During this time, we have recorded IMES data approximately four days a week. A typical recording session involves placing the monkey in a primate chair and then placing the monkey into a shielded Faraday chamber in front of the video screen used to cue the monkey. The monkey's arm was placed through the transmitting/receiving coil and then the monkey's hand was placed into the manipulandum. A typical recording session resulted in

approximately 30 minutes to 1 hour of EMG data simultaneously recorded with the finger switch closure data. The IMES EMG data were sampled at 1.26 kHz.

Instrumentation

The behavioral task was run on a National Instruments real-time embedded computer that interfaced with the data acquisition system using a PXI-digital/analog IO card. The user interface for controlling the experiment was provided via a second computer which communicated with the real-time embedded computer over Ethernet. The IMES EMG, finger switch closures, task events and parameters were recorded using a Cerebus data acquisition system (I2S, Salt Lake City, UT).

Algorithm

The acquired data were separated into training and testing subsets. In the training phase, the decode algorithm calculated the principal components of the spatiotemporal EMG energy patterns around known switch closures. It also calculated the centroids of the clusters formed by events of each type: thumb, index, and middle finger flexions in this principal component space.

Given the digitized EMG signals $x_{i,t}$ for time indices $t = 1, 2, \dots$ and IMES EMG channel indices $i = 1, 2, \dots, n$ ($n = 8$), the algorithm applied the nonlinear energy operator $(x_{i,t}^2 - x_{i,t-1}x_{i,t+1})$ to each $x_{i,t}$ and convolved the result with the low-pass Hamming kernel $h(t_f)$ with the cutoff frequency of 15 Hz, where t_f is the input to the filter. This yielded the short-time energy signals $e_{i,t} = h(t_f) * [x_{i,t}^2 - x_{i,t-1}x_{i,t+1}]$. An observation matrix of switch closure aligned data $\mathbf{S}(t)$ was then constructed by concatenating snippets of the short-time energy signals centered on switch closure times t . This observation matrix $\mathbf{S}$ was formed with each column comprising the concatenated EMG snippets surrounding a switch closure for all IMES channels minus the overall mean observation vector $\mathbf{s}$. Hence,

$\mathbf{S} = \langle e_{1,t-m}, \dots, e_{1,t+m}, \dots, e_{n,t-m}, \dots, e_{n,t+m} \rangle^T$, where m denotes the half-length of the window size and the angle brackets symbolize accumulation across trials without averaging. We used the value of m equivalent to 200 ms [8]. The principal component matrix U_d was computed from the truncated singular value decomposition of the observation matrix $U_d D_d V_d^T = \mathbf{S}$ with $d = 5$. An observation vector $\mathbf{s}$, a column from the switch closure aligned matrix $\mathbf{S}$, could then be projected onto the principal components as $\mathbf{u} = U_d^T \mathbf{s}$. Cluster centroids, i.e. the average projected observation vectors for each type of finger flexion, were then recorded as *thumb*, *index*, and *middle*. In the testing phase, the algorithm classified events into one of the three finger flexion categories given the IMES EMG signal with known switch closure times.

Observation vectors $\mathbf{s}$ from the testing data set were constructed for known switch closure times just as they were in the training phase. The algorithm then classified these observation vectors by associating them with the closest cluster centroid in the principal component space calculated in the training phase:

$$class(\mathbf{s}) = \arg \min_{j \in \{thumb, index, middle\}} \|\bar{\mathbf{u}}_j - \mathbf{u}\|$$

III. Results

There were no complications following IMES implantation and the monkey was completely recovered one week post-implantation. At eight days post-implantation the arm had healed enough for the monkey to safely begin performing the finger flexion task (Fig. 3).

The algorithm was run offline on training data sets and testing data sets recorded on the same day. The algorithm was never trained and tested on the same data set. Table II shows the intraday performance of the algorithm. The algorithm was also run offline with a training set from one day and tested on data sets that were recorded over multiple days. Table III shows the interday performance of the algorithm.

IV. Discussion

While other labs have shown the ability to accurately decode surface EMG during individual finger movements, to our knowledge this is the first time that EMG signals from implanted electrodes have been used to wirelessly decode individual finger movements with high accuracy [9]–[12]. The intraday results of the decode algorithm show that the IMES are able to record EMG during flexions of the thumb, index finger, and middle finger that is separable enough to accurately determine which of three fingers was flexed 89% of the time. This performance is 2.6 times above chance = 33.3%. Although the mean interday performance of the algorithm was 32.96% which is approximately chance (33.3%), the first two days in the interday table had decode percentages that were nearly 3 times chance. Following these two days, the decode performance dropped. There are two likely causes for poor intraday and interday decode performance. Firstly, a priori, the algorithm will perform better when the monkey makes stereotyped finger movements. Any time that the monkey presses a finger switch in a movement that is atypical of the training set, the algorithm has a greater chance of incorrectly classifying that switch closure. Atypical movements are therefore a possible explanation for the low performance of the algorithm on both intraday (e.g. day 12) and interday training-testing sets. A second potential cause for the decrease in decode performance is the variance in the location of the IMES in the transmitting/receiving coil. We have discovered that the location of the IMES within the transmitting/receiving coil is an important factor in the quality of the EMG signal. We believe that it is this interday variance of the IMES within the transmitting/receiving coil that decreased the ability to accurately decode finger flexions rather than nonstationarity of the IMES sensors within the muscle. However, these data suggest that for short interday periods the IMES EMG is fairly stable, but for longer interday training-testing periods the IMES EMG from the training set is different from the IMES EMG in the later testing sets. The intraday and short-term interday stability of the IMES recordings in non-human primates indicates that a person who has been implanted with IMES could control his/her prosthetic hand with a small training session every day or every other day.

The results from these experiments show that IMES are robust, stable recording devices that can provide multiple independent signals capable of controlling an arm or hand prosthesis. Additionally, IMES avoid many of the risks associated with percutaneous connectors and wires. The monkey's speedy recovery and absence of complications over many months suggests that IMES will be safe in human implantation. The results of this study have focused on a prosthetic application for those who have suffered a distal amputation. However, IMES may also provide effective prosthetic control signals for people who have suffered a proximal or complete amputation through implantation of the IMES into muscles that have undergone targeted innervation [13].

Another encouraging result of this work is that although we were unable to record from the thenar eminence, which plays a large role in thumb flexion, our PC analysis algorithm was

still able to accurately classify switch closures due to thumb flexion. This is because a single finger movement involves co-contraction of more than one muscle [14]. For example, in flexing a single finger, extensor muscles controlling adjacent fingers contract to stabilize the adjacent fingers and to keep them immobile as much as possible. Co-contraction and the recruitment of multiple muscles in finger movements means that it is not necessary for an IMES to be implanted into a muscle whose principal function is to produce a movement that is completely independent of other movements. The muscles into which the IMES are implanted are likely involved to different degrees in many different finger movements. This means that information regarding a certain finger movement is not solely found in one IMES but is spread over several IMES whose muscles were also recruited in that finger movement.

Currently we are working on improving the practicality of the decode algorithm by making the algorithm blind to switch closures. The algorithm will continuously detect both if a finger is flexed as well as classify which finger is flexed. Additionally, we will examine the performance of these algorithms in a real-time closed-loop implementation.

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Fig. 1.
Infrared photograph of the monkey's right hand in the manipulandum.

Fig. 2.
Time course and states during the finger flexion behavioral task.

Fig. 3. (Top) Radial view x-ray of the nine IMES implanted into the monkey's right arm. (Middle) dorsal view x-ray of implanted IMES. (Bottom) View of the monkey's right arm 20 days after implantation. Note there is only faint evidence of the incisions made for implantation (arrow).

Fig. 4. EMG from 8 IMES and switch closure data being simultaneously recorded on the Cerebus as the monkey performs the finger flexion task. TFlex=thumb flexion switch, IFlex=index finger flexion switch, MFlex=middle finger flexion switch.

Table I
Muscles Where IMES Were Implanted, and Their Function

Muscle	Function
FDP-deep	flex index (#2)
FDP-superficial	flex #3,#4,(#1-if 3 + 4 are flexed)
FDS	flex middle finger (#3)
FCr	wrist flexion
APL	thumb abduction
EDCI	extension of #4,#5
EDC	extension of #2,#3
wrist extensor	wrist extension
thenar eminence	thumb flex

FDP = flexor digitorum profundus, FDS = flexor digitorum superficialis, FCr = flexor carpi radialis, APL = abductor pollicis longus, EDC = extensor digitorum communis, EDCI = extensor digitorum communis to the index. Thumb and fingers are numbered from thumb to little finger #1 through #5.

Table II

Intraday Decode Algorithm Performance

Training Day	Train size	Testing Day	Test size	Weight	% Correct
1	63	1	53	0.482	88.68
2	28	2	110	1.000	98.18
3	69	3	98	0.891	81.63
7	20	7	5	0.045	80.00
8	77	8	46	0.418	89.13
12	57	12	21	0.191	38.10
14	79	14	90	0.818	88.89
15	83	15	99	0.900	95.96
Mean Weighted Intraday % Correct					88.70%

Train and Test sizes are the total number of switch closures recorded in that set. Weights were determined by normalizing each test size by the maximum test size and used to calculate the overall mean. % Correct is t percentage of the test size that was correctly classified into thumb flexion index finger flexion, and middle finger flexion.

Table III
Interday Decode Algorithm Performance

Training Day	Train size	Testing Day	Test size	% Correct
1	63	1	53	88.68
		2	138	96.38
		3	168	4.76
		7	25	16.00
		8	124	21.00
		12	78	11.54
		14	169	8.28
		15	182	17.03
1	116	2	138	87.68
2	138	3	168	39.29
3	168	7	25	80.00
7	25	8	124	64.52
8	124	12	78	62.82
12	78	14	169	34.91
14	169	15	182	70.88

Train and Test sizes are the total number of switch closures in that data set. % Correct is the percentage of the test switch closures that were correctly classified as thumb flexion, index finger flexion, and middle finger flexion. Mean % Correct when the algorithm was trained on day 1 and tested on all other days was 32.96% of 941 switch closures. Mean % Correct when the algorithm was trained on one day and tested on the subsequent day was 62.87%.