

1 used that information to trigger the stimulation sequence. Correct ECoG
2 classification resulted in the neuroprosthesis producing the correct hand
3 function (i.e., grasp and release).

4 **Results:** The neuroprosthesis classified ECoG signals correctly delivering
5 the correct stimulation strategy with 94.5 % accuracy.

6 **Conclusion:** The feasibility of using ECoG signals as a control strategy for
7 a neuroprosthesis for grasping was demonstrated.

8 **Key Words:** Neuroprosthesis for grasping, brain-machine interface,
9 electrocorticography, functional electrical stimulation, functional
10 neuromuscular stimulation.

11

12 INTRODUCTION

13 Functional electrical stimulation (FES) elicits muscle contraction
14 using electrical impulses and is used as a motor neuroprosthesis to facilitate
15 movement after SCI. The term neuroprosthesis will be used **here** to refer to
16 a motor neuroprosthesis.

17 Neuroprostheses are controlled using switches, linear variable
18 resistors, joysticks, position sensors, electromyographic signals, and **speech**
19 (1). A more intuitive method for controlling neuroprosthetic devices would

1 be to use brain activity. Brain-machine interfaces (BMIs) translate brain
2 signals into control commands for electronic devices.

3 Electrical signals reflecting brain activity have been used most
4 extensively to develop BMI systems. Non-invasive techniques for
5 recording the electrical activity of the brain include electroencephalography
6 (EEG). Invasive techniques allow the recording of local field potentials
7 (LFPs) reflecting the activity of a group of neighbouring neurons. LFPs can
8 be recorded using macroelectrodes placed on the surface of the brain,
9 resulting in electrocorticographic (ECoG) signals, and using
10 microelectrodes placed intracortically. These microelectrodes can also
11 record the activity of individual neurons.

12 Operating an EEG based BMI requires the user to change brain
13 activities voluntarily. For this, the user is often trained for up to several
14 months. Therefore, an important challenge in the development of BCIs is
15 minimizing the required training. For example, by using ECoG signals the
16 training time can be reduced to the order of minutes (2).

17 Spectral and temporal changes in brain activity elicited by voluntary
18 movement have been used to reduce the training time of a BCI user. These
19 changes have allowed the identification of specific movements and the
20 detection and estimation of kinematic parameters of the motion performed

1 (3).

2 Single cell recordings in monkeys and humans have yielded
3 important results in the detection and estimation of kinematic parameters
4 from brain activity making it possible to control computer cursors and
5 robotic arms using the activity from a group of neurons (4, 5). However,
6 there are concerns regarding the reliability and long term stability of single
7 neuronal recordings (6).

8 LFPs, including ECoG recordings, offer alternatives to single neuron
9 recordings. The changes in power of LFPs frequency components reflect
10 kinematic information of arm movements (7-10) and recently it was
11 possible to predict hand position from ECoG signals (6).

12 The convergence of the fields of neuroprosthetics and BCI appears
13 to be a natural next step in the development of these two fields. Using BCI
14 technology, a neuroprosthesis could detect the intention to perform a
15 specific movement and deliver the electrical stimulation to produce that
16 exact movement. The benefit of such a system would be enhanced further if
17 the user required little or no training to use this device.

18 Upper limb neuroprostheses (11-14) have been controlled by
19 individuals with quadriplegia using single cell recordings (15) and EEG
20 signals after training lasting between three days and four months (12). To

1

2 **Subjects**

3 Two subjects participated in this study. Subject 1 was a 67-year-old
4 woman implanted with subdural (i.e., ECoG) electrodes for the treatment of
5 essential tremor (Fig. 1a). The subject was recruited from the movement
6 disorder clinic at the Toronto Western Hospital and gave informed consent
7 to participate. The study was approved by the University Health Network
8 Research Ethics Board.

9 Subject 2 was a 35 year-old man with a complete cervical SCI (C6
10 level/ASIA B) and had received four weeks of FES therapy treatment for
11 restoring grasping function, as part of another study (16). He was able to
12 use his arms and wrists but had no hand movement. Subject 2 gave written
13 and informed consent to participate in this study as required and approved
14 by the Toronto Rehabilitation Institute Research Ethics Board. Figure 1b
15 subject 2 wearing the neuroprosthesis for grasping.

16 We certify that all applicable institutional and governmental
17 regulations concerning the ethical use of human volunteers were followed
18 during the course of this research.

19

1 **ECoG and Motion Recordings**

2 ECoG signals and arm movements were recorded simultaneously
3 from subject 1 during a single one-hour session three days after the initial
4 implantation of the subdural electrode. The subdural electrode (RESUME,
5 Medtronic3586, Medtronic, USA) had a single row of four platinum-iridium
6 disc contacts (4 mm diameter and 10mm center to center distance). The
7 electrode was implanted over the arm representation of the left motor
8 cortex, which was confirmed intra-operatively using electrical stimulation
9 delivered directly to the brain and observing contractions of the right upper
10 limb.

11 Monopolar ECoG signals were band **limited** (0.5 Hz – 500 Hz) and
12 recorded (sampling rate = 2 kHz , SynAmps2, Compumedics, USA). The
13 ECoG signals were down-sampled to 200 samples per second and
14 subtracted from each other to create differential signals using the recordings
15 from non-adjacent electrodes (e.g., contact 3 and contact 1) (17).

16 **Using only the right upper limb**, subject 1 performed wrist flexion
17 (WF), reaching to the right (RTR) and reaching to the left (RTL) after an
18 auditory cue and held the final position of the movement until a second
19 auditory cue. A motion sensor was placed over the dorsal aspect of the third

1 metacarpal of the right hand to record the movement using a six-
2 dimensional (X, Y, Z, roll, yaw and pitch) motion capture system (Fastrak,
3 Polhemus Inc., USA). Only position recordings (X, Y and Z) were used for
4 this study (17). Each movement was repeated at least 35 times and each
5 trial was visually inspected to identify mistrials, defined as: 1) a trial in
6 which the individual had performed a movement different from what had
7 been instructed; 2) the participant had started to move before the auditory
8 cue; or 3) the movement was not completed. Table 1 and Figure 2 show the
9 movements performed along with the number of trials used to conduct this
10 study.

11 We created a nearest neighbour classifier (Matlab, Mathworks,
12 U.S.A.) using five trials of each motor task to identify the performed arm
13 movements by analyzing the ECoG signals. The remaining trials were used
14 to test the neuroprosthetic system.

15 To classify the subdural signals we identified ECoG spectral
16 components correlated with the kinematic components of the arm
17 movement (Pearson correlation coefficient > 0.1 ; statistics degrees of
18 freedom = 600). The time resolved spectra were obtained using a
19 spectrogram (128-sample Hamming window, 128-FFT, and 127 point
20 overlap). The 20 frequency components with the highest correlation

1 coefficients were grouped using a histogram with bins representing
2 frequency bands of 10 Hz. Details of this process can be found in (17).

3

4

5 **Neuroprosthesis for Grasping**

6 The right hand of subject 2 was fitted with a neuroprosthesis to
7 generate palmar and lateral (key pinch) grasps (18). The neuroprosthesis
8 was designed and created specifically for this study using a Compex Motion
9 four-channel transcutaneous electrical stimulator (Compex S.A.,
10 Switzerland).

11 **The grasping movements** were achieved by stimulating: 1) *flexor*
12 *digitorum superficialis* and *flexor digitorum profundus* using two electrodes
13 connected in parallel to channel 1 (20 mA) to generate finger flexion; 2)
14 *flexor pollicis brevis* using channel 2 (14 mA) to generate thumb opposition;
15 and 3) *extensor digitorum communis* using channel 3 (22 mA) to generate
16 opening of the hand. Palmar grasp was obtained by stimulating channels 1
17 and 2, simultaneously. By stimulating channel 1 followed by channel 2,
18 500 msec later, the lateral grasp was achieved. Stimulation of channel 3
19 generated hand opening. In all cases, the stimulation frequency was set to

1 40 Hz and the pulse duration was 300 μ sec. Figure 3 depicts the stimulation
2 profiles to elicit the grasping synergies.

3 The **neuroprosthesis** had three accessible buttons (Buddy Button
4 5700 Series, Tash Inc., Canada) that subject 2 could activate with the dorsal
5 aspect of his left hand. Pressing button 1 or 2 elicited palmar grasp or
6 lateral grasp, respectively. A second activation of either of these switches
7 generated hand opening. Button 3 was used to turn the neuroprosthesis on
8 and off. A two-hour training period allowed the user to become
9 comfortable **using** the neuroprosthesis commanded with **the** three buttons.

10 Later, the accessibility buttons were disconnected from the
11 stimulator and reconnected to the ECoG classifier. With this modification,
12 pressing buttons 1, 2, and 3 resulted in the random selection and
13 classification of an ECoG signal recorded when subject 1 **had performed**
14 WF, RTR, and RTL, respectively. The classified trials excluded the
15 recordings used to create the classifiers. After the classifier determined
16 which ECoG signal had been extracted it commanded the neuroprosthesis to
17 perform the desired hand function or turn on/off the stimulator. Correct
18 classification of the ECoG signals resulted in the correct stimulation
19 sequence delivered by the neuroprosthesis. A diagram depicting the
20 complete implemented neuroprosthetic system is shown in Figure 4.

1 Subject 2 picked up 18 objects (19), shown in Table 2, requiring
2 palmar and lateral grasps. Each object was grasped and lifted from a table
3 using the neuroprosthesis. The participant held the objects in pronation and
4 supination and then released them. To test all of the available classes
5 (ECoG signals), the user was asked to turn the neuroprosthesis off and on
6 after grasping two objects consecutively.

7

8 **Classification Tests**

9 The accuracy of classification (as the number of trials in which the
10 system performed the action required by the user divided by the total
11 number of activations of the neuroprosthesis) was measured. The time
12 between the activation of a user switch and the issuing of the classification
13 result was also recorded.

14

15 **RESULTS AND DISCUSSION**

16 We confirmed the presence of ECoG spectral components correlated
17 with each one of the kinematic dimensions of the movements performed by
18 subject 1 (Table 3). Figure 5 shows histograms created by grouping 20

1 spectral components identified as the most strongly correlated with
2 kinematic recordings. The distribution of correlated frequencies was found
3 to be dependent on the type of movement performed by subject 1 ($p < 0.001$,
4 chi-squared statistic) suggesting that the recorded LFP activity is distinct for
5 each arm movement performed.

6 Subject 2 was able to use the neuroprosthesis with an accuracy of
7 94.5%. Most of the incorrect classifications occurred when the system was
8 attempting to classify trials corresponding to WF, as the confusion matrix
9 provided in Table 4 shows. Closer inspection of the kinematic recordings
10 revealed that the wrist flexion motion was less consistent than the reaching
11 movements. This was likely the cause of the misclassification. The average
12 time elapsed between the ECoG classification to the activation of the
13 neuroprosthesis was $1,870 \pm 109$ msec.

14 There are seven grasping styles and dozens of combinations which
15 can be generated using today's FES technology. However, providing a user
16 interface to control these functions independently remains a challenge,
17 regardless of the user's motor abilities. This is an unsolved problem in the
18 FES field. A BMI capable of identifying multiple movements has the
19 potential to command multiple grasps using a single interface.

1 In this work we presented a BCI system that uses ECoG signals to
2 control a neuroprosthesis for grasping. Activation of the neuroprosthesis
3 triggered an off-line classification process of a single ECoG trial. The result
4 of this classification triggered specific electrical stimulation sequences to
5 perform palmar and lateral grasps as well as turning the electrical stimulator
6 on and off. We believe that the short time required to create the system
7 (less than 60 minutes, including both the neuroprosthesis and BMI design)
8 along with the small number of trials used to create the classifier (i.e., five)
9 using activity from only four contacts to identify three different movements
10 performed with the same limb make this system unique.

11 The technology and procedures used in this study have a good
12 record of stability and reliability in clinical applications resulting in an
13 increased interest in the development of BCIs using ECoG signals.
14 However, it is still necessary to verify the long term performance of
15 subdural electrodes in BCI applications.

16 This work allowed us to explore our ideas of the integration of BMI
17 systems and FES, and run a true end-to-end system test on the use of ECoG
18 signals to control a neuroprosthesis for grasping. While several reports
19 describe the control of robotic or virtual systems with brain activities, we
20 selected this application due to its clinical prevalence; FES is technology

1 currently used to facilitate movement in persons with SCI. However, to
2 conduct our tests we could not justify implantation of subdural electrodes or
3 the instrumentation of an arm with a neuroprosthesis when these
4 interventions were not required for medical reasons. Because of these
5 ethical challenges the only possible solution was to use two subjects which
6 is why the ECoG signals used to trigger the neuroprosthesis were not
7 recorded from the same individual instrumented with the neuroprosthetic
8 system.

9 Although the movements identified from subject 1 were different
10 from the movements produced by the neuroprosthesis in subject 2, we
11 believe that this work brings us closer to a situation in which individuals
12 will be able to elicit a movement in their paralyzed limbs by attempting or
13 imagining that same movement. We feel confident that in future
14 implementations this discrepancy can be overcome and that the
15 neuroprosthesis will be able to produce the exact movement identified from
16 ECoG recordings. By doing this, the level of transparency of interaction
17 between the user and a neuroprosthetic device will increase dramatically.

18 Voluntary movement-related changes in power in the beta band
19 appear to show temporal differences (20) in patients with ET. These
20 differences may affect the correlation values on which the classification

1 method is based. However, we have tested successfully the presented
2 method with individuals with Parkinson's disease and essential tremor and
3 we are confident that the employed method will work with different patient
4 populations.

5 While our system operates on ECoG signals recorded while actual
6 arm movements were performed, our immediate work will focus on
7 developing a classifier able classify imagined and/or intended movements to
8 control the neuroprosthesis. We also plan to develop a system capable of
9 identifying in real-time specific arm movements from ECoG recordings.

10

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TITLES AND LEGENDS TO FIGURES

- 15 **Figure 1.** Participants. a) X-ray image of Subject 1 with subdural
16 electrodes implanted on the motor cortex over the representation of the
17 upper limb. b) Subject 2. c) and d) Surface stimulation electrodes used to
18 elicit palmar and lateral grasps.

1 **Figure 2.** Movements performed by subject 1. These included wrist flexion
2 (WF), reaching to the right (RTR) and reaching to the left (RTL).

3 **Figure 3.** Stimulation sequences for a) palmar grasp and b) lateral grasp.
4 Both stimulation sequences used three stimulation channels. Each channel
5 stimulated a different muscle or nerve at different times to generate
6 synergistic movements. (I) Pressing button three was used to turn the
7 stimulator on through a random selection and classification of ECoG signals
8 recorded while subject 2 was reaching to the left (RTL). (II) Pressing
9 buttons 1 or 2 caused the system to classify randomly selected ECoG
10 signals recorded while subject 2 was performing wrist flexion (WF) or
11 reaching to the right (RTR), respectively. The result of the classification
12 triggered a specific stimulation sequence to elicit palmar or lateral grasp.
13 (III) Grasping was sustained until either button 1 or 2 were pressed a second
14 time which resulted in a change in the stimulation delivered to facilitate
15 hand opening. (IV) After three seconds the stimulation stopped and the
16 neuroprosthesis returned to an idle state. (V) Button 3 could also be used to
17 turn the stimulator off through the classification of a randomly selected
18 ECoG signal recorded when subject 2 was reaching to the left. Figure
19 adapted from (18).

20 **Figure 4.** Complete experimental setup. The user pressed one of three

1 buttons to control the neuroprosthesis. Each button was associated with a
2 dataset of ECoG signals recorded previously. The system randomly
3 extracted a single trial of the corresponding dataset which was classified by
4 a nearest neighbour classifier. The result of the classification process was
5 then used to trigger a stimulation sequence. When the classification was
6 successful the correct stimulation sequence was delivered by the
7 neuroprosthesis. Conversely an incorrect classification would result in an
8 incorrect action taken by the neuroprosthesis.

9 **Figure 5.** Histograms resulting from grouping the 20 spectral components
10 identified as the most strongly correlated with kinematic recordings. Each
11 bin in the histogram corresponds to a frequency range of 10 Hz. Values
12 are expressed as probabilities after dividing the magnitude of each column
13 by the total number of spectral components used for each plot (20). The
14 amplitude of each column represents the probability that a spectral
15 component within the frequency range defined by the bin is correlated with
16 movement. Each histogram was different and unique for each one of the
17 movements performed by subject 1.

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TABLE CAPTIONS

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TABLE I. Movements performed by subject 1 along with duration of movement, available trials and movement ranges. The movements included wrist flexion (WF), reaching to the right (RTR) and reaching to the left (RTL).

TABLE II. Objects used to test the neuroprosthesis. The different objects required the use of both palmar and lateral grasp.

TABLE III. Correlation coefficients between ECoG spectral components and kinematic recordings. The correlation values were obtained by averaging over all dimensions (X.Y.Z) of movement and were translated into p-values via Fisher's combined probability test.

TABLE IV. Confusion matrix for the implemented classifier. Each element in the matrix shows the percent ratio between the number of trials available for each movement performed by subject 1 and the outcome of the classifier. The classifier had the greatest number of misclassifications of

- 1 ECoG signals recorded when subject 2 was performing WF and classified as
- 2 RTR. The second with the largest category with classification errors was
- 3 RTL misclassified as RTR. The classifier however performed well
- 4 identifying the ECoG signals recorded while the subject was performing
- 5 RTR.

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TABLE I. MOVEMENTS PERFORMED BY SUBJECT 1 ALONG

4

WITH DURATION OF MOVEMENT, AVAILABLE TRIALS AND

5

MOVEMENT RANGES.

Task	Duration (msec)	Number of Good Trials	Range of Motion (mean \pm standard deviation)		
			X (cm) (up-down)	Y (cm) (left-right)	Z (cm) (proximal- distal)
WF	219.4 \pm 64.1	20	0.96 \pm 0.42	1.22 \pm 0.8	1.6 \pm 1.1
RTR	208.8 \pm 48.8	25	17.7 \pm 0.62	34.9 \pm 3.2	9.4 \pm 0.6
RTL	253.5 \pm 44.6	23	7.16 \pm 1.24	32.3 \pm 2.4	5.32 \pm 0.9

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2 **TABLE II. OBJECTS USED TO TEST THE NEUROPROSTHESIS.**

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Required Grasping Approach	Object
Palmar	Mug, book, 355 ml soft drink can (full), mobile phone, wooden blocks with high friction surface (100g, 200g, and 300g), wooden blocks with wooden surface (100g, 200g, and 300g), wooden blocks with low friction surface (100g, 200g, and 300g)
Lateral	Sheet of paper, paper bag, die, credit card, pencil

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**TABLE III. AVERAGE CORRELATION VALUES BETWEEN
ECoG SPECTRAL COMPONENTS AND KINEMATIC
RECORDINGS**

	WF	RTR	RTL
Average correlation coefficient	0.42 ± 0.03	0.43 ± 0.04	0.45 ± 0.05
p value (Fisher's combined probability test)	<0.005	<0.005	<0.005

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**TABLE IV. CONFUSION MATRIX FOR THE IMPLEMENTED
CLASSIFIER.**

	WF	RTR	RTL
WF	91.67%	8.33%	0%
RTR	0%	100%	0%
RTL	0%	5.45%	94.55

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17

a)



b)

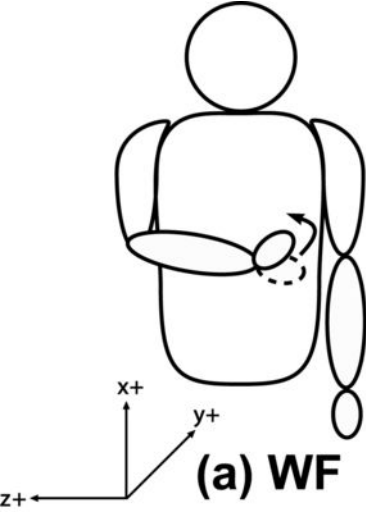


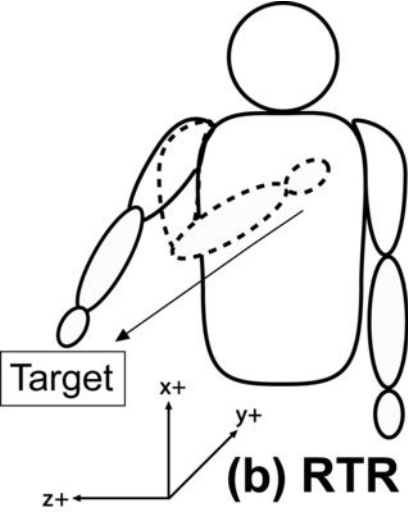
c)

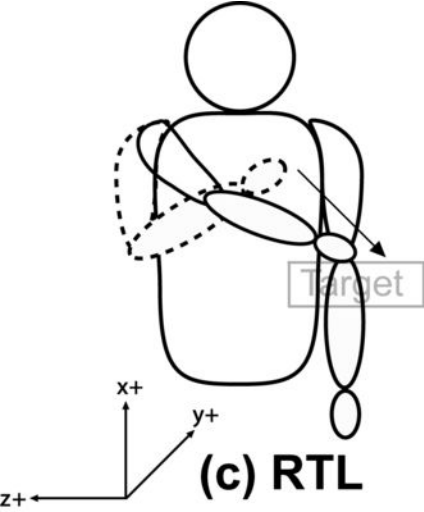


d)

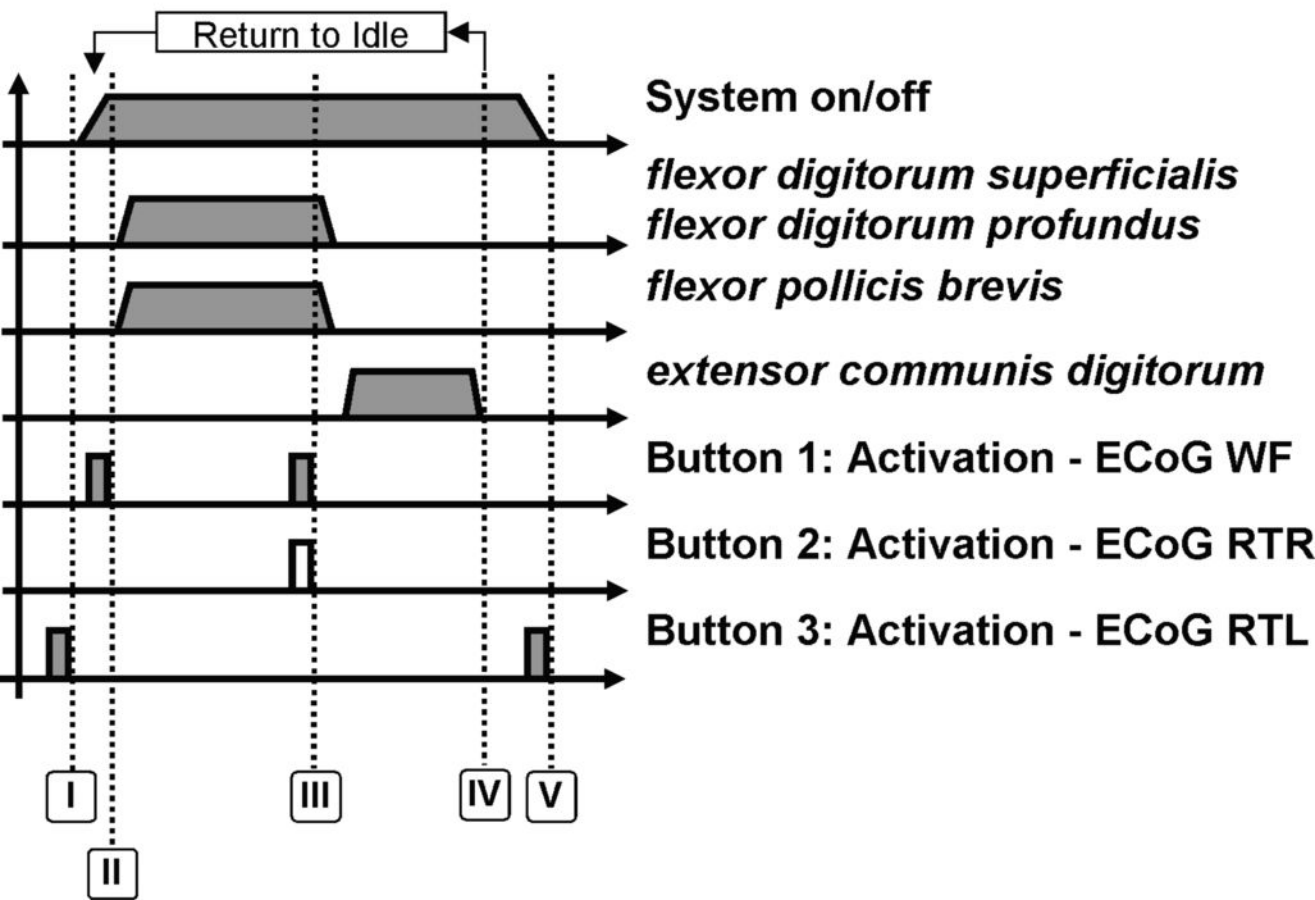






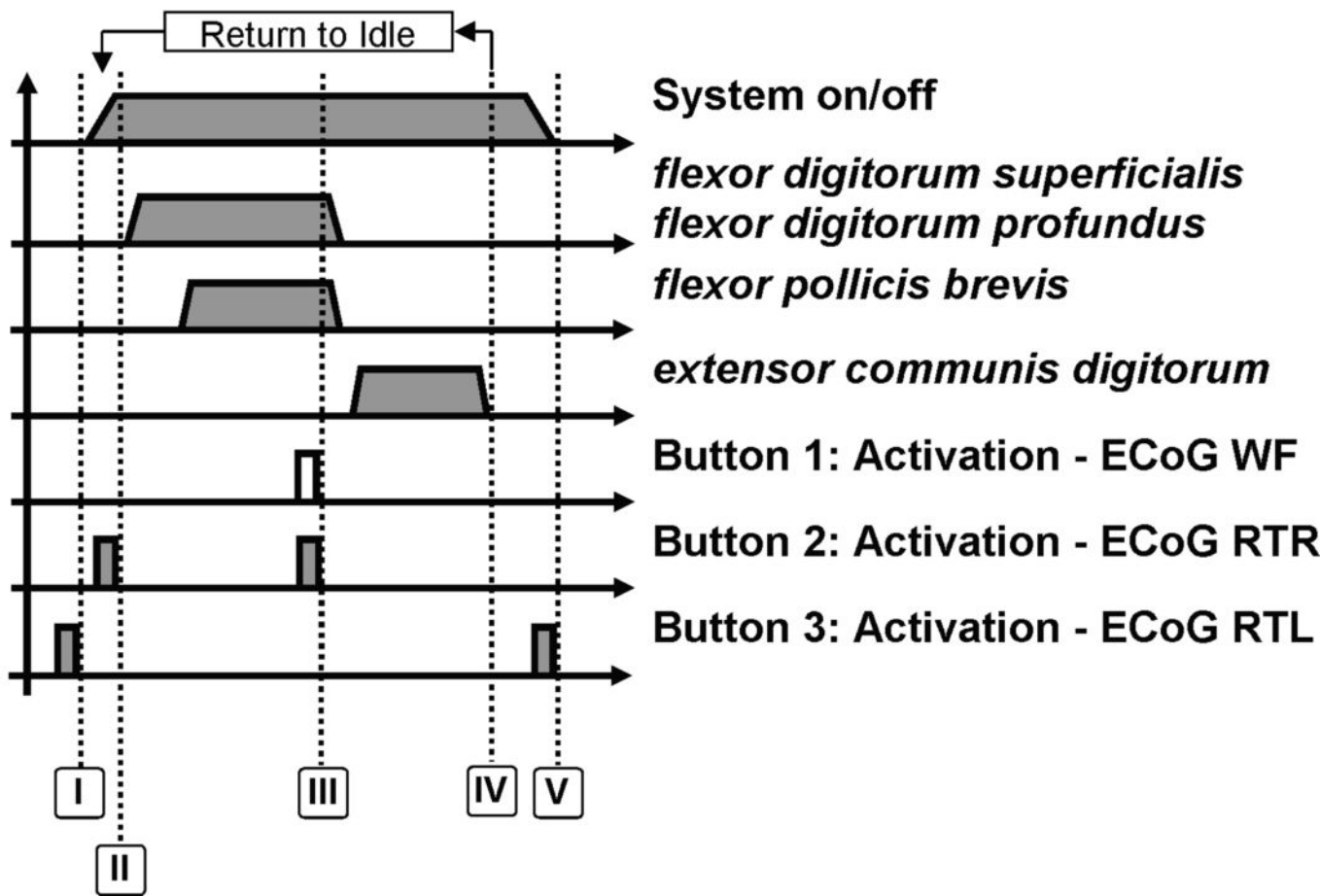


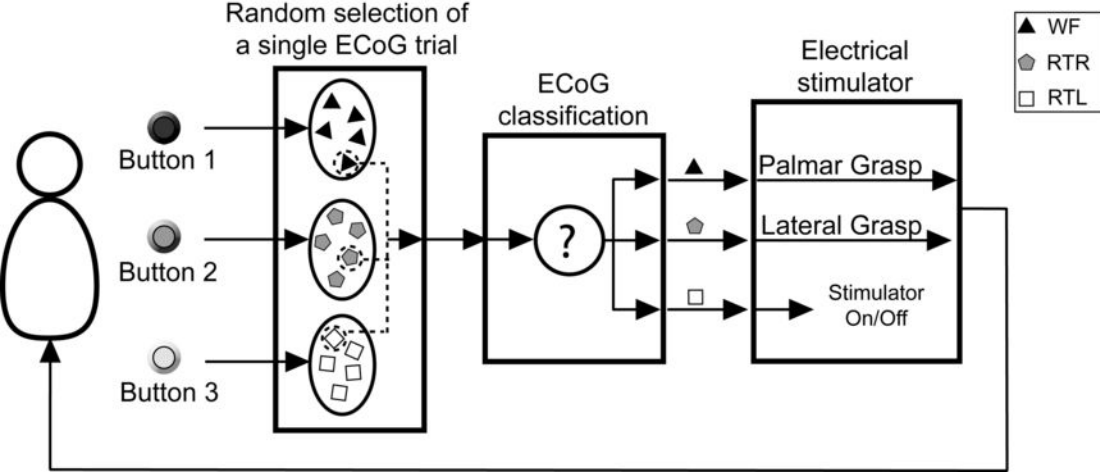
a) **Stimulation Sequence for Palmar Grasp**

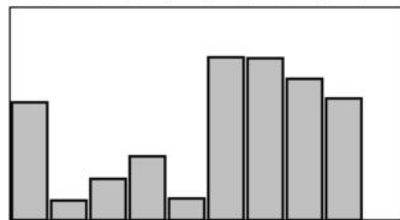
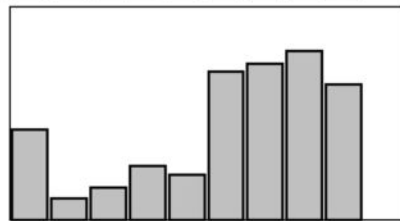
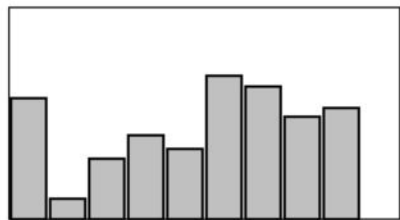


b)

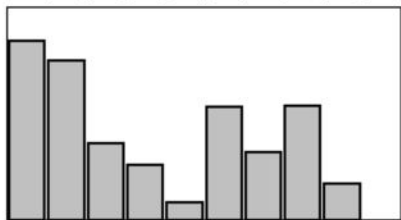
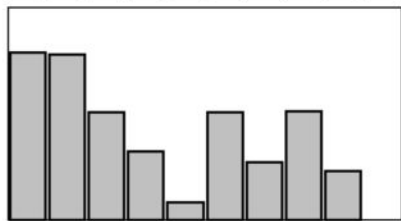
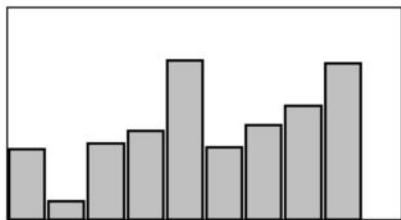
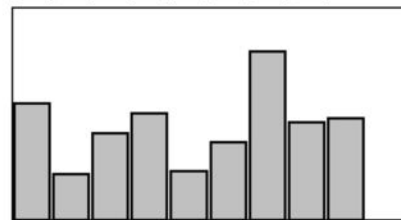
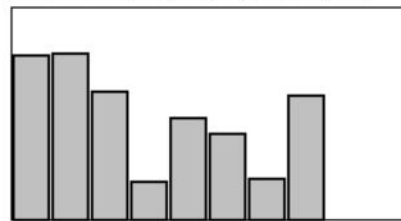
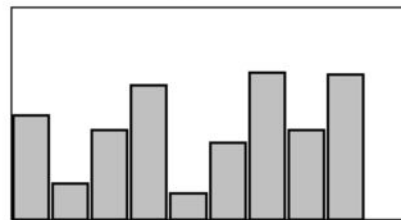
Stimulation Sequence for Lateral Grasp





Wrist Flexion

0-10
10-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100
Hz

Reaching to the Right**Reaching to the Left**

X

Y

Z