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The Tracking of Reaches in Three-Dimensions

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Abstract— Prosthetic devices to replace upper limb function have made great progress over the last decade. However, current control modalities for these prosthetics still have severe limitations in the degrees of freedom they offer patients. Brain machine interfaces offer the possibility to improve the functionality of prosthetics. Current research on brain machine interfaces is limited by our understanding of the neural representations for various movements. Few electrophysiology studies have examined the encoding of unconstrained multi-joint movements in neural signals. Here we present a system for the high-speed tracking of multiple joints in three dimensions while recording, optimizing and decoding neural signals.

I. Introduction

Many simple daily activities, such as picking up a cup of coffee or opening a door, depend on visually guided reaching. The loss of the ability to reach can have devastating effects on the mobility and independence of patients. Each year in the US, approximately 16,000 people lose their ability to control their arms due to spinal cord injury [1]. In addition to this over 3000 people suffer the loss of part of their upper limbs through amputation [2].

For patients suffering from the paralysis of a limb, functional electrical stimulation of the paralyzed muscles has been shown to be able to restore partial functionality [3-5]. For patients suffering from the complete loss of a limb, current research has been focused on developing a motorized robotic replacement for the arm [6-8].

Both these approaches have shown great promise. However, the best way to give users control of such devices has not yet been established. Control of prosthetic devices has been accomplished with varying success through many different methods. These include through the use of foot switches [9], throat control [10], the measurement of electromyograms of remaining functional muscles [11,12], or of reinnverated muscles [13] and through the measurement of neural signals [14]. Of these methods, brain machine interfaces (BMIs) which measure neural signals have shown potential to offer finer control with greater degrees of freedom over prosthetic devices. These BMIs measure neural activity through electrodes placed either non-invasively on the surface of the skull, or invasively with electrodes placed on the surface of the cortex, or penetrating the cortex [14-16].

However, before these BMIs can transition from the laboratory to a commercial device, more information about the neural mechanisms that control unconstrained multi-joint movements need to be determined. The importance of understanding these mechanisms has been acknowledged for decades [17,18]. The frontal cortices have been shown to encode movement direction and speed. The posterior parietal cortex encodes spatial representations of movements [19]. However to date, most studies have been limited by technology to only examine reaching in two-dimensions, often through the control of a manipulandum. Furthermore, many studies have looked at reaching in the absence of saccadic eye movements. There is currently a paucity of data on how neural signals represent and control reaching in space. If a clinical device is to give patients significant functionality, it is essential that we understand the neural mechanisms of making coordinated reaches in three-dimensions.

This paper presents a three-dimensional hand tracking system that allows for the optimization of neural recordings and work towards understanding the neural mechanisms underlying reaching in three-dimensions with the goal of achieving a high performing movement decoder.

II. METHODS

A. Experimental Preparation

Two adult male rhesus macaques (*Macaca mulatta*) were used in the study. Each subject was behaviorally trained for several months to perform reaches and saccades to cued locations. A recording chamber was implanted in one monkey over the frontal cortex. Thirty-two microelectrodes with center-to-center electrode spacings of 1.5 mm, were lowered into cortex via a semi-chronic microdrive (SC32-1, Gray Matter Research, USA). Electrodes had an initial impedance of 0.7-1.5 MΩ at 1 kHz (Bak Electronics, USA). The semi-chronic drive allowed for independent bidirectional movement control of each electrode. This

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control of the movement of the electrodes allows for the optimization of depth on the recorded neural signals.

Neural signals were amplified and digitized at 30 kHz using 16-bits of resolution with the lowest significant bit equal to 0.1 µV (NSpike NDAQ System, Harvard Instrumentation Lab, USA.; x10 gain headstage Multichannel Systems, Germany).

All surgical and animal care procedures were approved by the New York University Animal Care and Use Committee and were performed in accordance with the National Institute of Health guidelines for care and use of laboratory animals.

B. Three-Dimensional Arm Tracking

Subjects were trained to wear an elastine glove. Infrared light emitting diodes (LEDs) were attached to the middle of each finger of the glove, with additional LEDs placed on the back of the palm and on the forearm. The LEDs flashed asynchronously and were monitored via four 12.4 megapixel infrared-cameras sampling at 480 frames/s (IMPULSE Motion Capture System, Phasespace Inc., USA). The cameras were mounted radially around the reaching arm of the subject (Fig. 1) to allow for the most complete coverage of reach movements. Once detected, LED marker positions were synchronized to the neural recordings using a common clock signal. The system allows for up to 128 markers to be tracked with sub-millimeter accuracy, however for this initial study only eight were used. Velocities and accelerations were then calculated off-line by taking the first and second derivatives of the marker positions. A movement decoder was then used decode movement features from the neural data.

C. Behavioral Task

Monkeys performed reach and saccade movements for liquid rewards. Eye position was constantly monitored with an infrared optical eye tracking system (ISCAN, USA) and the beginning and end positions of reaches were recorded via a touch-sensitive screen (ELO Touch Systems, USA). Visual stimuli controlled via custom LabVIEW (National Instruments, USA) were presented via an LCD screen (Dell Inc, USA).

Subjects were trained to perform a center-out task. Each subject was trained to saccade to red targets, reach to green targets and perform coordinated reach and saccade movements to yellow targets. Each trial started when the subject placed both hands on proximity sensors located directly in front of them. During a baseline period, a red square and a green square were presented centrally, and the subjects were required to maintain touch on the green square while fixating on the red square for 500 - 800 ms. A yellow square was then flashed in one of eight locations in the subject's periphery (10°) for 300 ms. The subjects maintained fixation and touch for another 1000 - 1500 ms

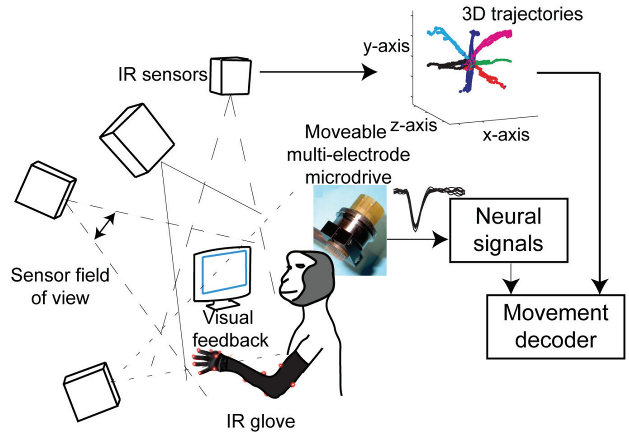

Fig. 1 – Schematic of the three-dimensional hand tracking and neural recording system. Infrared LEDs were attached to a glove worn by the subject. These LEDs are monitored via four infrared cameras placed around the reaching arm of the subject.

after which the initial red and green squares were extinguished cueing the subject's to reach and saccade to the target. A juice reward was delivered after subjects held fixation and touch at the target for 300 ms.

D. Movement Goal Decoder

Reach and saccade movement goals were decoded off-line from single trials of neural data recorded across the electrode array. Features were extracted from the power of the multiunit activity through singular value decomposition. The singular value decomposition was then used to project the signal on a 32 dimensional subspace.

After the features were extracted from the neural signals, the neural activity for movements to different targets was modeled using a multivariate Gaussian distribution with a diagonal covariance matrix. To decode the movement goals from the neural activity of a given trial we accumulated the posterior probability of the activity given each model. The movement goal model that gave the highest probability was chosen as the decoded movement goal. All models and performance parameters were estimated using leave-one-out cross-validation.

III. Results

Reach movement trajectories were recorded from the two subjects while they performed coordinated reaches and saccades. The average reaction time for reaches was 328 ± 3 ms (mean ± standard error of the mean), and the average reach duration was 213 ± 3 ms.

A. Reach Movement Trajectories

Understanding reach metrics is a vital goal for developing more sophisticated prosthetics. Being able to track reach

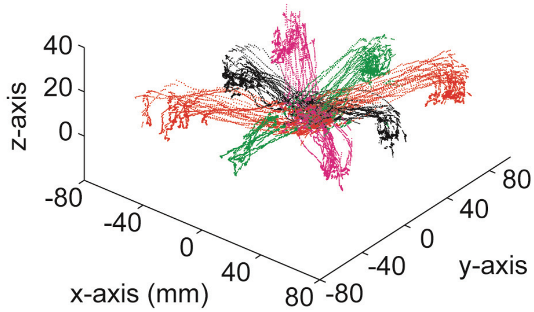

Fig. 2 Example reach trajectories for the center-out task. Visually guided reaches are performed from a central location out to eight different targets located 10° from the initial location. The trajectories shown are for movements of the LED placed on the middle of the index finger used by the subject to touch the cued targets.

metrics online will allow us to correlate different stages of the reach with the neural mechanisms that guide them. Further, by having the ability to move electrodes allows for the optimization of recording signals in depth.

Both subjects showed similar reach trajectory profiles to the targets. Figure 2 shows example movement trajectories of one of the subject's index finger moving to the eight peripheral targets from a central location. The index finger was used by the subject to touch the cued targets. These example trajectories demonstrate that the three-dimensional hand tracking system is accurately monitoring arm and hand movements.

Interestingly, the velocity profiles of the reaches were slightly different to the eight cued targets. Figure 3 shows the average velocity traces for the reaches to the eight targets. Movements to all targets except for the target directly below the starting hand position exhibited smooth bell-shaped profiles. Reaches to the target below the starting hand position resulted in smaller movement velocities as the subjects tended to drag their hands down to the target.

Finally, Figure 4 presents the average acceleration for the reaches presented in Figure 3. The subject's reaches showed an initial burst of acceleration followed by a phase of deceleration as the reach was guided to the target. Similar to the velocities, accelerations to the target directly below the starting point were smaller due to the subjects dragging their hands.

B. Neural Decoding

Movement goals for the visually guided reaches were decoded off-line. The performance of decoding 471 trials is shown in Figure 5. The best decoding performance was for movements that were performed to the contra-lateral direction to the recording chamber (86 % correct decodes for movement goals to the top left target). Decoding errors were primarily due to incorrect decodes to neighboring directions.

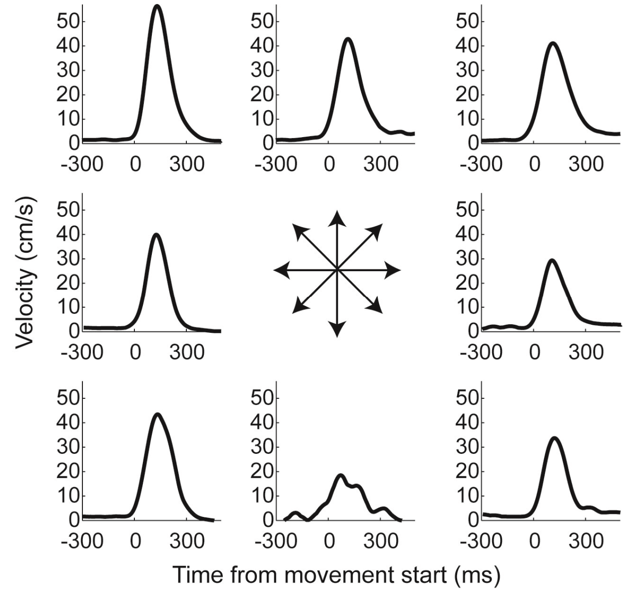

Fig. 3 Average reach velocities for center out movements in the eight directions tested. Reaches exhibited vastly different velocity profiles for movements in different directions. The velocity profiles are presented in the same spatial orientation as the reaches performed by the subjects.

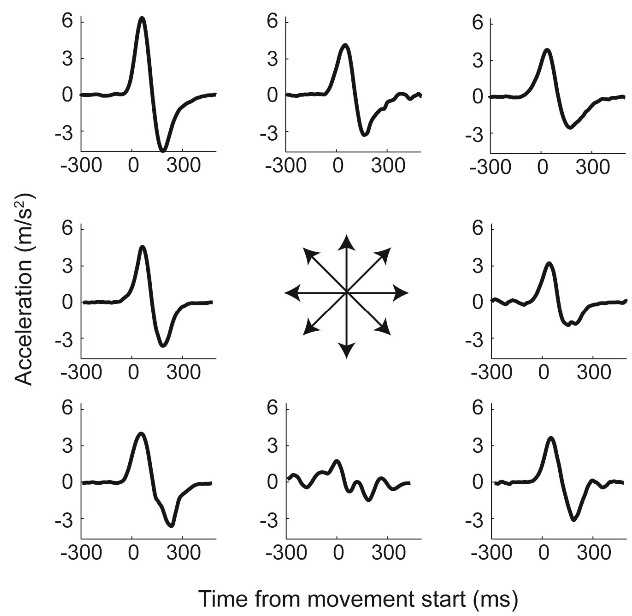

Fig. 4 Average accelerations of the index finger for center-out reaches to the eight targets. The acceleration profiles are presented in the same spatial orientation as the reaches performed by the subjects.

IV. Discussion

In this paper we have presented a new test platform that performs high accuracy measurements of reach trajectories in three-dimensions. These measurements will allow us to

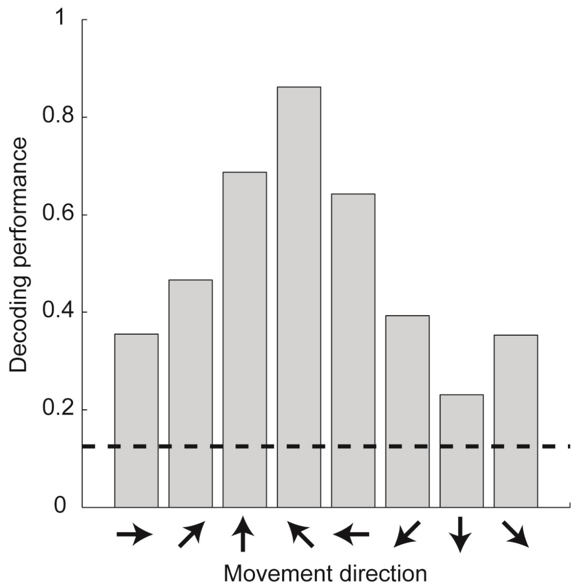

Fig. 5 Performance of off-line decoding of visual guided reaches for movements to the eight targets. Chance decoding performance (12.5 %) is marked with a dashed black line.

test for the neural correlates of reaching in different brain areas and to optimize the recorded signal in depth. However, while we have shown that we can accurately track hand and arm movements, while decoding movement goals of visually guided reaches, this is the just first step towards the understanding of the neural signatures that underlie reaching.

The optimal control of prosthetics will require an understanding of the neural signatures of unconstrained multi-joint movements. These experiments will lead to further work in which arrays of moveable electrodes will be implanted in reach-related areas such as the dorsal premotor cortex, while we decode movement goals for multiple joints on-line in the absence of actual movements. Furthermore, the ability to accurately decode movements in all directions will be significantly improved by implanting electrodes bilaterally.

Finally before BMI's can move from the laboratory to become a commercial clinical device, work is needed to improve the modeling/decoding algorithms to allow amputees to use the device without the need to first train the device with a test data set of actual reach movements.

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