Observation-based training for neuroprosthetic control of grasping by amputees

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Abstract—**Current brain-machine interfaces (BMIs) allow upper limb amputees to position robotic arms with a high degree of accuracy, but lack the ability to control hand pre-shaping for grasping different objects. We have previously shown that low frequency (0.1 – 1 Hz) time domain cortical activity recorded at the scalp via electroencephalography (EEG) encodes information about grasp pre-shaping. To transfer this technology to clinical populations such as amputees, the challenge lies in constructing BMI models in the absence of overt training hand movements. Here we show that it is possible to train BMI models using observed grasping movements performed by a robotic hand attached to amputees' residual limb. Three transradial amputees controlled the grasping motion of an attached robotic hand via their EEG, following the action-observation training phase. Over multiple sessions, subjects successfully grasped the presented object (a bottle or a credit card) in 53±16 % of trials, demonstrating the validity of the BMI models. Importantly, the validation of the BMI model was through closed-loop performance, which demonstrates generalization of the model to unseen data. These results suggest 'mirror neuron system' properties captured by delta band EEG that allows neural representation for action observation to be used for action control in an EEG-based BMI system.**

I. Introduction

Recent strides in robotic prosthetics for the upper limb potentially allow amputees to control an ever-increasing array of dexterous tasks [1], [2]. In addition to positioning the arm in space, an important challenge is to be able to control the pre-shaping of fingers during grasping. Recent advances such as targeted muscle reinnervation (TMR) [3] and myoelectric control using residual limb muscle activity [1] offer exciting possibilities, but lack the intuitive and natural control offered by brain-machine interfaces (BMIs) [4]. Intracranial BMIs have been demonstrated to control arm positioning with a high degree of accuracy, but have a single degree of freedom to control grasping [5]–[7]. Implementing an intuitive and noninvasive BMI for grasping has remained a challenge, however.

In our previous work we show that grasping movements can be decoded from electroencephalographic (EEG) activity, a noninvasive modality to record cortical potentials at the scalp [8], [9]. Frequency-domain features such as the mu band (8-13 Hz) or gamma band (30 – 50 Hz) are modulated by movement, and have been traditionally used in noninvasive BMIs. We demonstrated that low delta band (0.1 -1 Hz) also contains significant information about grasping, albeit in the time domain. Further, we showed that principal components (PCs) of finger kinematics are decoded with the same level of accuracy as finger joint angles during grasp pre-shaping. In a closed-loop BMI scenario, it is advantageous to control the kinematic PCs as they allow grasp pre-shaping with fewer degrees of freedom.

However, a key challenge in translating this technology to the clinical domain has been to construct such BMI models in the absence of overt hand movements in amputee subjects. Studies have shown that there may be a shared neural substrate between action observation and action performance, known as the mirror neuron system [11]. There is evidence from previous studies that in healthy human subjects and primates, such a shared neurophysiology allows us to substitute overt movement with action observation during training of a BMI model [12]–[14]. Here, we show results of using such an observation-based BMI training method for grasping in amputees.

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II. Methods

A. Experimental Design and Data Acquisition

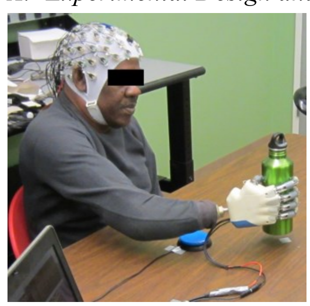

Fig. 1. Experimental setup. Amputee subjects were fitted with the robotic hand to their residual limb sockets. 64 channel EEG was recorded simultaneously.

Three right-hand transradial amputees (2 males, 1 female; ages 56-76) participated in this study approved by the IRB at the University of Houston. Subjects A, B and C performed two, twelve and four sessions respectively, with each session being performed on a different day. Each session consisted of a training phase (creation of BMI model) and a testing phase (closed loop control using the BMI model). Subject B performed six additional sessions with only the testing phase, which will not be considered for this study. Subjects were fitted with an anthropomorphic robotic hand (IH2 Azurra, Prensilia s.r.l., Italy) to their residual limb sockets (Fig. 1). Sixty-four channel EEG (Brain Vision LLC, USA) was recorded at 100 Hz during the experiment (Fig. 1). Simultaneous recording of EEG and control of the robotic hand was achieved using the BCI2000 framework [15].

The IH2 Azurra robotic hand has five degrees of freedom: one each for the flexion-extension of the thumb, index finger

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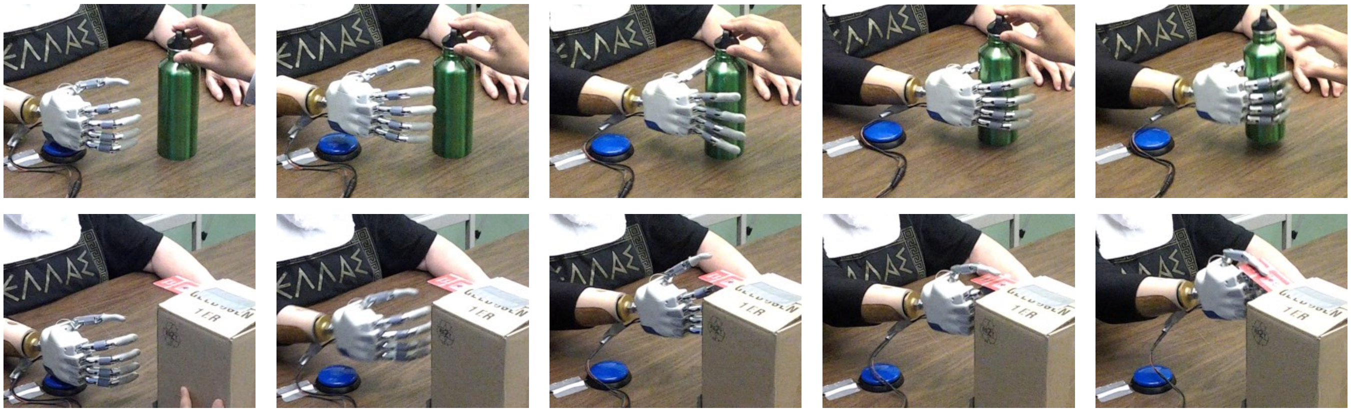

Fig. 2. Grasp trajectories in the observation-based training phase. Top row (time proceeds from left-to-right) shows snapshots in time of the grasp trajectory during a cylindrical grasp. Bottom row shows the grasp trajectory for a lateral grasp.

and middle finger, one for the combined flexion-extension of the ring and little finger, and one for the thumb rotation [2]. The robotic hand uses a differential mechanism via which a single degree of freedom (dof) is used to control both the MCP (metacarpal-phalangeal) and PIP (proximal inter-phalangeal) finger joints in such a way that when the MCP joint encounters an obstruction (due to grasping an object), the PIP continues to flex until the object is grasped [1] Finger kinematics for a single degree of freedom were specified at an 8-bit resolution, with 0 and 255 corresponding to open and fully flexed positions respectively. Nominally, two synergies of grasping based on principal component analysis of the joint angles were identified based on previous work as a) the correlated movement of the flexion-extension across all fingers and the thumb, and b) the thumb rotation [8]. These two synergies will henceforth be referred to as PC1 and PC2

Subjects were seated in front of a table with their attached robotic hand resting on a switch. The experiment involved grasping two objects with the robotic hand: a bottle and credit card, meant to evoke a cylindrical and a lateral grasp respectively. Each trial consisted of a researcher presenting an object to be grasped at a pre-determined comfortable distance away from the resting position. Following presentation of the object to be grasped in a trial, subjects self-initiated hand transport towards the object (Fig. 2).

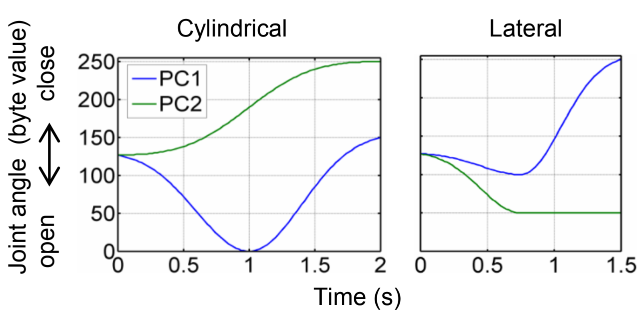

Fig. 3. PC1 and PC2 trajectories set during training phase for action observation.

During the training phase, initiation of hand transport triggered a pre-determined grasping sequence in the robotic hand, suitable to the object being presented. The pre-determined finger joint trajectories were created so as to have typical human grasp aperture time profiles seen during grasping [16]. A Gaussian profile was used for PC1 activation, while a Gaussian profile was used for PC2 velocity, with a total time lengths 2 s and 1.5 s respectively (Fig. 3). The thumb rotation (PC2) was held constant during the second half of the trajectory in the case of the lateral grasp. Subjects timed their hand transport in conjunction with the hand pre-shaping, so that by the end of the hand transport, the object was grasped. Subjects were instructed to imagine themselves controlling the hand pre-shaping and grasping. In addition to the visual feedback, subjects were asked to imagine kinesthetic feedback as well. The grasp was held steady for 2 s, followed by an opening of the grasp and a return to the resting position (reverse of the grasping trajectory). During the grasp release trajectory, subjects transported the hand back to its resting position. Subjects performed 100 trials during the training phase. The order in which objects (bottle or card) were presented varied in a pseudorandom fashion.

A mapping between the 64-channel EEG data and the two synergies (PC1 and PC2) was created using data recorded in the training phase. In the testing phase, this mapping was applied to EEG to make real-time predictions of PC1 and PC2, allowing closed-loop control of the robotic hand pre-shaping. Initiation of hand transport by the subject, following presentation of an object to be grasped, triggered the start of closed-loop control. Thereafter, subjects had 5 s to grasp the presented object. The outcome of each trial was marked as a 'success' or 'failure' depending on whether the subject was able to grasp the object or not. Monitoring current drawn by the actuator motor for each degree of freedom allowed us to detect when an object was grasped, since the current drawn spikes if resistance due to the object is encountered. Once an object was successfully grasped, closed loop control ceased and the grasp was held steady for 3 s. Following either outcome, the hand shape was returned to resting position according to the pre-determined grasp release trajectory suitable for the presented object, as used in the training phase.

Real-time data acquisition and control of the robotic hand were achieved using the BCI2000 framework [15]. Although EEG was recorded at 100 Hz, data packets were sent from the amplifiers at a rate 50 Hz, constraining the real-time loop to

20 ms. Consequently, the robotic hand control was also sampled at 50 Hz.

B. Signal Processing

A causal filter was used to band-pass filter data between 0.1 -1 Hz. This was implemented as cascaded high pass and low pass 2^{nd} order Butterworth filters. The maximum group phase delay in the passband was 300 ms. Both training phase and testing phase EEG were filtered in this manner. After the training phase, EEG and kinematics were extracted and processed offline in MATLAB (The Mathworks, Inc., USA). A lag of 100 ms was introduced in the EEG so that kinematics at time *t* aligned with EEG at time *t-100* ms. This was done to account for the cortico-spinal delay and the lag estimate was based on previous BMI studies [17]. EEG data were standardized by their mean and standard deviation. Kinematics were upsampled to 100 Hz (from 50 Hz) using the MATLAB *pchip* (piecewise cubic hermite interpolating polynomial) method, followed by a transformation to PC1 and PC2 by multiplying with the PC coefficient matrix for the pre-determined grasp trajectories. PC1 was the average of the 4 finger and thumb flexion values, and PC2 was the thumb rotation value. Data were then segmented into movement periods, from movement onset to completion of grasp, and concatenated along trials.

These data were then used to construct a linear mapping using robust linear regression, which mitigates the effect of outliers by weighting them less. This method was implemented in MATLAB (The Mathworks, Inc., USA) using the *robustfit* function which uses iteratively reweighted least squares with a bisquare weighting function. PC1 and PC2 were modeled independently as a linear combination of EEG sensor data:

$$PC_i[t] = \beta_{i0} + \sum_j \beta_{ij} S_j[t - 100\ ms]$$

where $PC_i[t]$ is the i^{th} PC being decoded at time t, β_{ij} are the model parameters and S_j are the processed EEG from the j^{th} electrode. In the testing phase, this linear mapping was used to predict PC1 and PC2 values from filtered and standardized EEG. Standard deviation from the training phase was used to scale EEG. These PC predictions were then scaled using a gain parameter so that when transformed back to the kinematic space of joint actuators, they represent ‘properly’ scaled movements. A few trials were conducted before the testing phase to manually tune the gain parameters according to the subjects’ preference of the range of motion. If the final predicted kinematic actuator values were outside the range 0-255, they were set to either 0 or 255 depending on the direction in which the range was exceeded.

III. Results

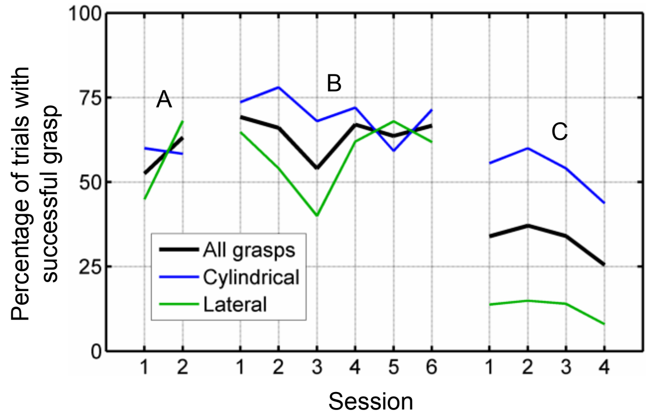

Fig. 4. Performance was measured as the percentage of trials in which grasps were performed successfully. Letters above traces indicate subject identifier. Black traces show the success rate across both the grasp types, blue and green traces show the same for cylindrical and lateral grasps. Mean performance was 58%, 64% and 32% for subjects A, B and C respectively.

Subjects performed closed-loop control of the robotic hand in the testing phase using the linear model constructed after the training phase. The outcome of each trial in the testing phase was either a successful grasp within the 5 s provided, or a failure to grasp. Examples of successful trials are shown in Fig. 4. The percentage of successful grasps in the testing phase was used as the performance metric. The average success rates across sessions were 58%, 64% and 32% for subjects A, B and C who performed two, six and four sessions respectively (Fig. 5). We also investigated success rates for individual grasp types, and found that for

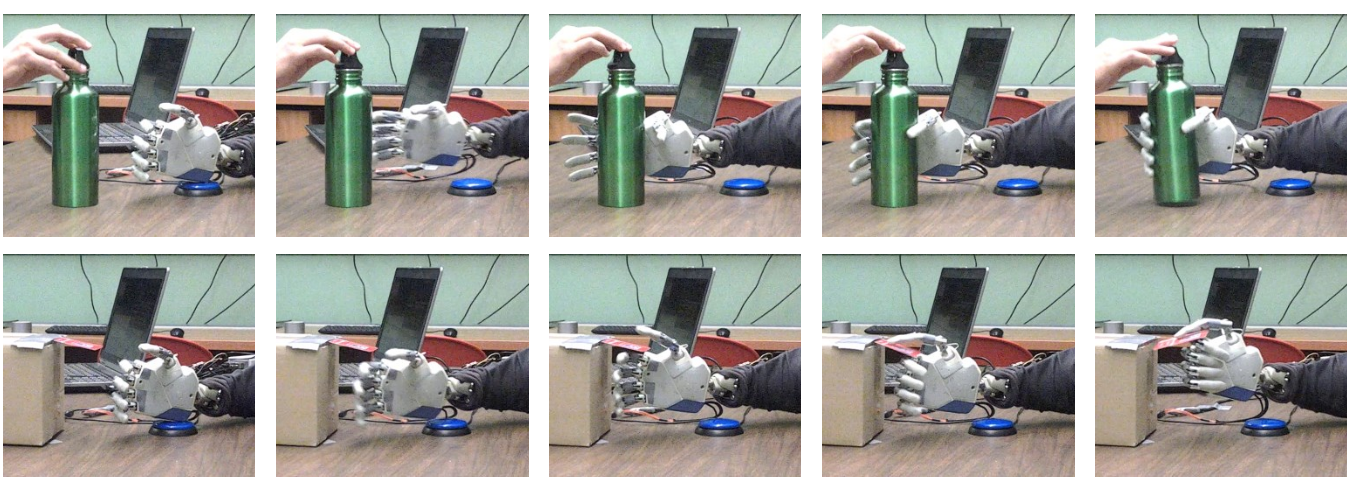

Fig. 5. Grasp pre-shaping with closed-loop control. Top row shows a trial with successful cylindrical grasp. Bottom row shows a lateral grasp under closed-loop control.

subjects B and C, the bottle was grasped better than the card. This may be because of the precision required for the card grasp, whereas the cylindrical grasp is a whole-hand grasp.

The training phase to calibrate the BMI model was performed in each session to assess the consistency of model performance across multiple days. Fig. 4 shows that within a subject, the performance is consistent across sessions. Further, BMI models were validated with the closed-loop scenario, confirming their generalizability to unseen data.

IV. Discussion

In the absence of overt kinematics in amputees, being able to train BMI models presents a challenge for researchers. The mirror neuron system has been used to train BMI models in primates for 3D reaching movements [18], [19]. A similar approach has been used to calibrate intracortical BMI to control positioning of an arm in space in humans [5]. Bradberry et al. have shown that it is possible to use action observation to determine a mapping between noninvasive EEG activity and cursor movement on a computer screen [14]. The results here show that this approach is successful, in amputees, to train BMIs for EEG to movement mappings for dexterous grasping tasks using a robotic hand as well.

To conclude, we show in this study that observing grasping actions performed by a robotic hand can be used to train time-domain EEG-based neural interfaces. Furthermore, these BMI models are generalizable to closed loop grasping with consistent performance across sessions. Importantly, these results represent the closed-loop task performance immediately after training, and provide the 'baseline' performance upon which the brain may improve. To explore these ideas further, we are conducting longitudinal 'test phase (closed-loop) only' sessions to investigate the adaptation of the brain to a fixed BMI model over sessions, and the corresponding changes in BMI performance with the prosthetic hand.

References

[1] C. Cipriani, C. Antfolk, M. Controzzi, G. Lundborg, B. Rosén, M. C. Carrozza, and F. Sebelius, "Online myoelectric control of a dexterous hand prosthesis by transradial amputees," *Neural Syst. Rehabil. Eng. IEEE Trans.*, vol. 19, no. 3, pp. 260–270, 2011.

[2] C. Cipriani, M. Controzzi, and M. C. Carrozza, "The SmartHand transradial prosthesis.," *J. Neuroeng. Rehabil.*, vol. 8, no. 1, p. 29, Jan. 2011.

[3] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *JAMA J. Am. Med. Assoc.*, vol. 301, no. 6, pp. 619–628, 2009.

[4] J. L. Contreras-Vidal, A. Presacco, H. A. Agashe, and A. Paek, "Restoration of whole body movement: toward a noninvasive brain-machine interface system.," *IEEE Pulse*, vol. 3, no. 1, p. 34, 2012.

[5] L. R. Hochberg, D. Bacher, B. Jarosiewicz, N. Y. Masse, J. D. Simeral, J. Vogel, S. Haddadin, J. Liu, S. S. Cash, and P. van der Smagt, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, 2012.

[6] J. L. Collinger, B. Wodlinger, J. E. Downey, W. Wang, E. C. Tyler-Kabara, D. J. Weber, A. J. McMorland, M. Velliste, M. L. Boninger, and A. B. Schwartz, "High-performance neuroprosthetic control by an individual with tetraplegia.," *Lancet*, vol. 6736, no. 12, pp. 1–8, Dec. 2012.

[7] M. Velliste, S. Perel, M. C. Spalding, A. S. Whitford, and A. B. Schwartz, "Cortical control of a prosthetic arm for self-feeding.," *Nature*, vol. 453, no. 7198, pp. 1098–101, Jun. 2008.

[8] H. A. Agashe and J. L. Contreras-Vidal, "Reconstructing hand kinematics during reach to grasp movements from electroencephalographic signals.," *Eng. Med. Biol. Soc. (EMBC), 2011 33th Annu. Int. Conf. IEEE*, vol. 2011, pp. 5444–7, Jan. 2011.

[9] H. A. Agashe and J. L. Contreras-Vidal, "Decoding the evolving grasping gesture from electroencephalographic (EEG) activity," *Eng. Med. Biol. Soc. (EMBC), 2013 35th Annu. Int. Conf. IEEE*, vol. 2013, pp. 5590–3, 2013.

[10] J. M. Carmena, M. A. Lebedev, R. E. Crist, J. E. O'Doherty, D. M. Santucci, D. F. Dimitrov, P. G. Patil, C. S. Henriquez, and M. A. L. Nicolelis, "Learning to control a brain-machine interface for reaching and grasping by primates.," *PLoS Biol.*, vol. 1, no. 2, p. E42, Nov. 2003.

[11] G. Rizzolatti and L. Craighero, "The mirror-neuron system.," *Annu. Rev. Neurosci.*, vol. 27, pp. 169–92, Jan. 2004.

[12] H. A. Agashe and J. L. Contreras-Vidal, "Observation-based calibration of brain-machine interfaces for grasping," in *International IEEE EMBS Conference on Neural Engineering*, 2013, p. In publication.

[13] D. Tkach, J. Reimer, and N. G. Hatsopoulos, "Observation-based learning for brain-machine interfaces.," *Curr. Opin. Neurobiol.*, vol. 18, no. 6, pp. 589–94, Dec. 2008.

[14] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Fast attainment of computer cursor control with noninvasively acquired brain signals.," *J. Neural Eng.*, vol. 8, no. 3, p. 036010, Jun. 2011.

[15] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 6. pp. 1034–1043, 2004.

[16] U. Castiello, "The neuroscience of grasping.," *Nat. Rev. Neurosci.*, vol. 6, no. 9, pp. 726–36, Sep. 2005.

[17] T. J. Bradberry, R. J. Gentili, and J. L. Contreras-Vidal, "Reconstructing three-dimensional hand movements from noninvasive electroencephalographic signals.," *J. Neurosci.*, vol. 30, no. 9, pp. 3432–7, Mar. 2010.

[18] R. Wahnoun, S. I. H. Tillery, and J. He, "Neuron selection and visual training for population vector based cortical control," *Engineering in Medicine and Biology Society, 2004. IEMBS '04. 26th Annual International Conference of the IEEE*, vol. 2. pp. 4607–4610, 2004.

[19] R. Wahnoun, J. He, and S. I. Helms Tillery, "Selection and parameterization of cortical neurons for neuroprosthetic control.," *J. Neural Eng.*, vol. 3, no. 2, pp. 162–71, Jun. 2006.