HOW SIMILAR ARE THE NEURAL PATTERNS WHEN OBSERVING GRASPING HAND POSTURES TO THE BEHAVIORAL PATTERNS WHEN EXECUTING THE GRASP?

Andreea I. Sburlea [1], Gernot R. Müller-Putz[1]

[1] Institute of Neural Engineering, Graz University of Technology, Graz, Austria

E-mail: {andreea.sburlea, gernot.mueller}@tugraz.at

ABSTRACT: It is well-known that human neural representations of grasping movement observation and execution share similarities. However, it remains unclear to what extent neural patterns of movement observation relate with behavioral covariates of the movement, such as muscle or kinematic activity, or with categorical models that describe hand posture or object properties. In this study, we explored the relation between EEG neural representation of observing a large variety of hand-object interaction images and two representations of the observed movement's execution: the behavioral covariates and categorical models. We found that the EEG representation of the observation phase was correlated with the muscle representation during the execution most strongly in the movement holding phase. Furthermore, we found similarities with the categorical model that reflects the shape and the size of the object. With these findings we gain a joint understanding of the relation between movement observation and execution and a mean to facilitate an intuitive control of neuroprostheses in motor impaired individuals.

INTRODUCTION

Movement is the main way we can interact with the world. The motor system is involved in all types of movements, including speech, walking, reaching, grasping and many others. In particular, the ability to perform grasping movements plays an essential role in independent everyday activities. Spinal cord injury (SCI) or stroke can cause motor impairments that hinder the execution of these movements. Therefore, great effort is devoted towards the control of robotic limbs or neuroprostheses in people with motor impairments [1], [2]. Since these individuals cannot execute the desired movements, they can instead attempt or imagine the movement. When performing these tasks similar brain activations have been found as in an actual movement execution task, leading to the discovery of the mirror-neuron system [3], [4]. The existence of the neural mirroring activity and the observation-execution matching has been first reported in macaques [5], [6], and later in humans [7], [8], [9]. In humans, the mirroring system is thought to play a role in understanding others' actions [10] and in a range of social cognitive processes, such as action planning or anticipation [11], [12], perceiving intention [13], [14], [15], imitation [16], or in other social interactions [10], [17].

Moreover, the observation of movements or hand-object interactions, even in static pictures has been shown to involve the motor and visuo-motor areas [4], [18].
In individuals with SCI, we lack information about muscle activations during movement execution and for the control of neuroprostheses we can rely on the EEG correlates of the imagination or attempt of hand movements [19]. We have recently shown that brain activity shares similar activation with the muscle activity during grasping and holding phases of the movement [20]. While observation and execution also share similar brain activations, the relation between the brain patterns associated with the observation of hand postures and the actual muscle components during movement execution remains unclear. We believe that a better understanding of the relation between these movement stages and their covariates could lead to an intuitive control of neuroprostheses or robotic limbs.
Explaining how behavior is implemented by neural mechanisms is a challenging task. One possibility is that tackling both of these challenges simultaneously may be more tractable than addressing each separately at its own level of analysis [21]. Hence, it is essential to establish a reliable relation between observation and execution in terms of both neural and behavioral representations.
In this study, we explored the similarity between the neural representation while observing static images of hand-object grasping interactions and the associated behavioral representation (in terms of muscle and kinematic activations) while executing the observed grasping interaction. We also categorized the grasps based on the shape and size of the object, position of the thumb relative to the palm, in addition to the more conventional grasp type categorization in power, pincer and intermediate, and then built three different categorical models. We applied representational similarity analysis (RSA) [22], [23] to investigate the similarities among the effects of the neural, behavioral (muscle and kinematic) representations and categorical models at different time stages of grasping movements.

MATERIALS AND METHODS

A previously recorded dataset has been used in this study [20]. The dataset contains simultaneously acquired neural (EEG) and behavioral (muscle and kinematic) data of thirty one participants, in a task that involves observation and

execution of different grasping movements. The experimental protocol was approved by the ethical committee of Medical University of Graz (approval number: 29–352 ex16/17), and all subjects gave written informed consent before participating in the experiment. Fig. 1A illustrates the structure of the experimental protocol.
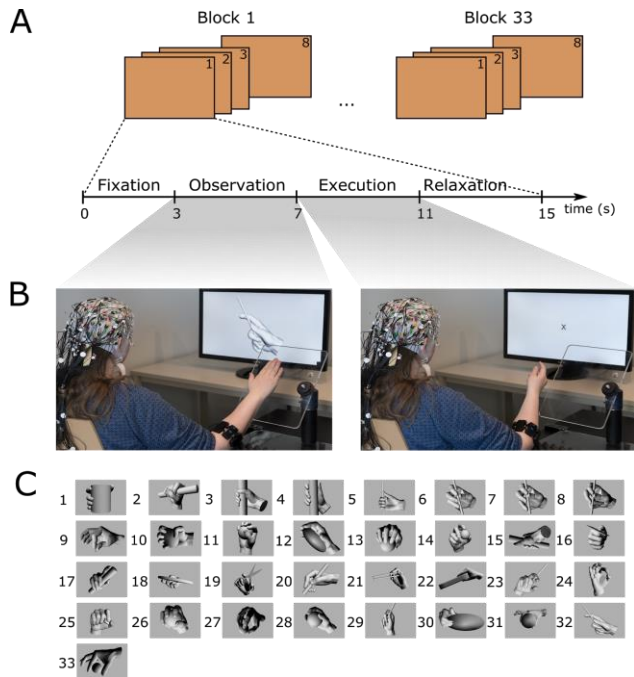

Figure 1: (**A**) Experimental protocol. Each of the 33 blocks contained eight consecutive repetitions (trials) of the same grasp. Each trial had four phases: fixation (three seconds long), observation (four seconds long), execution (four seconds long) and relaxation (four seconds long). (**B**) Experimental setup. Photos of one participant during the observation and execution phases, and the materials used during recording. (**C**) Pictograms of the grasping movements.

During the fixation period, participants were instructed to focus their gaze on a cross located in the middle of the screen and avoid eye movements for three seconds. Next, during the observation phase which lasted four seconds, participants were presented with a static image showing a hand in a final grasping position together with the grasped object. During this observation phase, participants could move their eyes and observe the shape and size of the object, as well as the position of the fingers and the overall shape of the hand. During the fixation and observation phases, as well as during the break, participants rested their hand on a transparent, custom-made plexiglass hand support, shown in Fig. 1B. We built this hand support to reduce hand fatigue and recorded the resting position using the Leap Motion optical tracking device. During the execution phase which was also four seconds long, participants were instructed to focus their gaze on the "x" symbol located in the middle of the screen and to lift their hand from the resting support, move it slightly to the left and perform the grasping movement that they had observed during the previous phase. The acquisition of the blocks was divided in 4 parts. The

first three parts contained 8 blocks and lasted 16 minutes each, while the last part contained 9 blocks. After each part, we offered longer breaks to the participants. The total duration of one recording was, on average, an hour and a half. The participant shown in Fig. 1B gave her informed consent for the photo to be made available in the conference publication. Fig. 1C shows the pictograms of the 33 grasping movements with their ordinal numbers. The order of the grasping conditions (blocks) was randomized among participants.

In the dataset, EEG and EOG data was recorded using a 64-channel ActiCap System with two BrainAmp amplifiers (BrainProducts, Germany). The ground sensor was placed on AFz and the reference sensor on the right mastoid. To record the muscle activity, we used a Myo armband (Thalmic Labs Inc., Canada). The armband was located on the right arm close to the elbow, above the extrinsic hand muscles. To record the kinematics related to the grasping movements, we used the Leap Motion controller (Leap Motion Inc., CA, USA).

For all data preprocessing and analyses, we used Matlab R2016b (Mathworks, Inc. USA). EEG data was first filtered using a Butterworth fourth-order, zero-phase, band-pass filter between 0.1–40 Hz and then downsampled to 100 Hz. We rejected the trials in which the task was incorrectly performed (e.g., start of movement before the associated cue). From the EEG data we extracted the first seven seconds associated with the fixation and observation period and performed a similar cleaning processing pipeline as described in [20]. Next, we computed the time-frequency representation using Morlet wavelets with a resolution of 0.5 Hz in between 0.1 and 40 Hz. To compute the ERD/S patterns, we used the fixation period (1-3s) as baseline.

The eight EMG data channels were processed using Hilbert transform, standardized using z-score and, finally, the envelope of the data was computed. From the signals recorded using the Leap Motion controller, we used nineteen joint angles for the rest of the analysis. These joint angles correspond to the five proximal (one artificially created for the thumb and four for the other fingers), five intermediate and five distal joints of each finger, as well as the four in-between fingers joints. Given the high degree of correlation between some of the explored joints, we applied principal component analysis (PCA) to reduce the dimensionality of the kinematic data. We retained for each subject the first five components, which accounted, on average, for more than 95% of the data variance.

For each of the three acquisition modalities (EEG, EMG and joint angles), we averaged single repetitions of the same grasp condition both within subject and between subjects leading to one group-level representation per grasp condition. For the averaging of the joint angles, we used the circular mean, as implemented in the CircStat toolbox [24].

For the extraction of the behavioral features of interest we defined three temporal windows in the movement execution segment. The windows were consecutive and each window was 500 ms long, which is in line with the latencies of the grasping phases previously reported in the literature [25]. The first window was associated with the reaching and pre-

shaping of the hand, and it started from the movement onset. The second window was associated with the finalization of the grasping movement. The third window contained information about the holding position of the grasping. From the three windows we extracted the features of interest from the two behavioral data acquisition modalities: EMG and joint angles. For the neural data, we extracted the 4-second window corresponding to the observation phase.

Our strategy consisted in comparing the neural information from the observation period with the behavioral information from the three windows of the execution period.

For the EEG pattern extraction, we implemented a searchlight technique to extract ERD/S patterns simultaneously at different spatial locations and frequency bands. We present the searchlight approach in more detail in [20]. For the analysis, we defined 31 centroids in the channel space and 26 in the frequency space. One neighborhood, in either of the spaces, had five members: one centroid and four equidistant neighbors, and had 2 members in common with any other neighbourhood. The two-dimensional window defined by the channel and frequency neighborhoods was slid across the two dimensions. Each frequency neighborhood corresponded to a 2 Hz-wide band and had an overlapping step of 0.5 Hz.

We applied the searchlight technique on the entire 4-second long window from the observation segment. All the information within a two-dimensional window was concatenated into a vector. This vector defined the EEG pattern of activity for the region with a given centroid in space and in frequency. For the EMG envelope and for the kinematic joint angles, the behavioral patterns resulted from the concatenation of all channels (components) of data over each of the three inspected temporal windows.

For each of the three temporal windows, we compared the behavioral patterns of different grasping conditions with the neural patterns of the observation period. We used $1\text{-}r$ (where r is the Pearson correlation) as the distance metric between the patterns of different conditions. Next, we ranked and scaled the distances between 0 and 1, and computed the representational dissimilarity matrix (RDM) [23] between pairs of grasping conditions. In addition to the neural and behavioral representations, we also implemented categorical models. These models were built from previous categorizations based on the type of grasp, position of the thumb relative to the palm, defined in the largest pre-existing taxonomy of static and stable grasps [26], and on the shape and size of the object [20]. The RDMs of these categorical models were binary representations, which contained a 0 for each pair of stimuli falling into the same category and a 1 for each pair of stimuli falling into different categories. We define as reference RDM the neural representation during the observation phase and as candidate RDMs both the behavioral representations during the execution phase and the categorical models.

To evaluate the consistency of our obtained RSA effects we conducted a bootstrap analysis with 500 iterations. We performed the bootstrap analysis on a pool of 31 different samples corresponding to our subject number. In each iteration, we replaced the 31 samples with other randomly pulled 31 samples. Through bootstrapping, we could estimate the confidence interval, as the variance of the mean distance between the reference and candidate RDMs in our population of 31 subjects. We report the 95% confidence interval (CI) of the procedure together with the obtained mean effect.

RESULTS

We computed the reference representations based on the searchlight analysis of the time-frequency representation of the EEG data during the observation period. We then computed the representational similarity between the reference (EEG) RDM and the behavioral (EMG and joint angles) representations in the three time windows of interest of the movement execution period: hand pre-shaping ($0 - 0.5$ s), reaching of the final grasping posture ($0.5 - 1$ s) and holding ($1 - 1.5$s). We also computed the RSA between the reference representation and the three categorical models.

Fig. 2 describes, at a population level, the results of the representational similarity analysis between the reference neural representation (during the observation period) and the candidate behavioral representations (described by muscle and joint angles information) and the categorical models (type of grasp, position of the thumb relative to the palm and shape of the object). We observed that the reference neural representation during movement observation is more similar (smaller $1\text{-}r$ distance) to the muscle than to the kinematic representation during movement execution. This similarity becomes even stronger during the holding phase of the movement, in which the hand maintains the final grasping posture ($1\text{-}r = 0.69$, 95% CI: [0.66, 0.72]) in the mu and low beta frequency bands in parietal and occipital areas. In the previous movement phases the values of similarity were: $1\text{-}r = 0.74$ during hand pre-shaping and $1\text{-}r = 0.71$ during the reaching period of the final grasping posture. Moreover, from the categorical models, the reference representation is more similar to the model that encodes the shape and the size of the object also in mu and beta frequency bands over parieto-occipital brain regions ($1\text{-}r = 0.79$, 95% CI: [0.77. 0.8]) compared to the other categorical models.

In Fig. 3, we focused on the previously observed effects and assessed their significance at the population level. Fig. 3A shows the topographical representation of the similarity effects relative to the behavioral representations (top and middle) and categorical model Object shape (bottom). Next, we conducted a bootstrapping analysis and we show in Fig. 3B the effects and their 95% confidence interval.

DISCUSSION

In this exploratory study, we investigated the similarities among neural, behavioral and categorical representations of observing and executing a large repertoire of unique grasping movements [26]. Using a searchlight approach, we extracted EEG patterns from the observation period at different frequencies and brain areas, and compared them with behavioral (muscle and kinematic) representations of the executed movements, as well as with three categorical
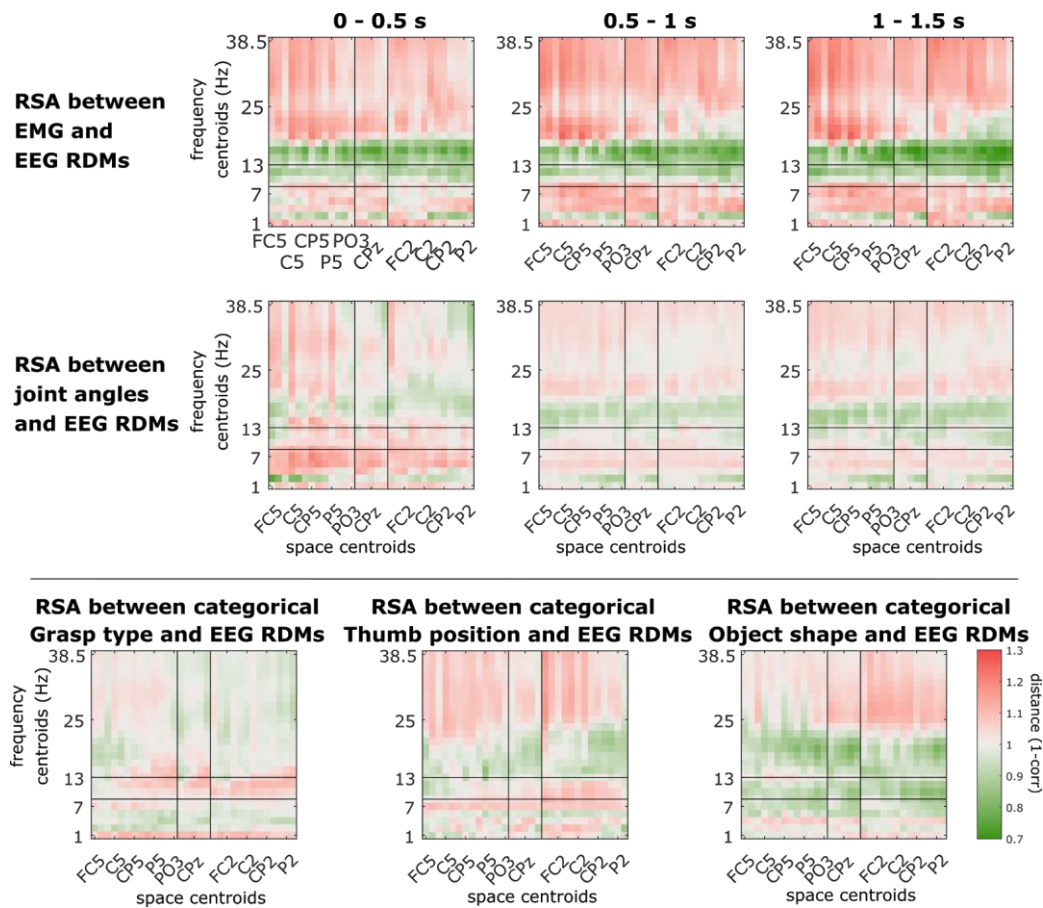
Figure 2. Representational similarity analysis between the candidate representations and the reference representations extracted through a searchlight implementation. The vertical black lines mark the area covered by the midline centroids. The horizontal lines mark the mu frequency band. The space centroids are sorted from periphery-to-midline and anterior-to-posterior.

models that describe the type of grasp, the position of the thumb during grasping and the intrinsic properties of the object (shape and size).

We found that the parietal and occipital areas encode information about grasping movements during the observation period. Moreover, we found that the muscle representation during the holding phase of the movement showed similarities with the EEG representation during the observation period in the mu and low beta frequencies. We also found similarities between the EEG representation during observation and the categorical model that describes the shape and the size of the objects. These similarities were more pronounced in the contralateral parietal and occipital regions in the mu and beta frequency bands. EEG activation in parietal and occipital brain regions in mu and beta frequency bands have been reported also by [27] when observing hand-object interactions. According to the ideomotor theory [28], [29], actions are represented by their perceived effects. Hence, external or internal events can trigger the corresponding actions.

During the observation of grasping hand postures, the neural processes related to the concept of movement result from peripheral sensations generated by previous knowledge about how the movement would be executed, plus proprioception [29]. In our study, all the observed grasping postures were familiar to the participants. It has been shown that attention to kinesthetic perception of the movement also triggers activations of motor areas in similar frequency bands [30]. Desynchronization of the mu and beta rhythms is a commonly used measure of motor cortex activation [31], [32] in movement observation tasks. Mu desynchronization has been identified as a possible measure of the mirroring system [33]. We also found activations in the frequency range of the mu band (8-13 Hz) both in the parietal and occipital brain areas. Indeed, the two activations originate from distinct processes, the first being related to the motor planning and the second to the visual processing. Furthermore, Pfurtscheller et al. [31] made a division into lower and upper alpha (mu) bands. The upper alpha band is shown to be associated to stimulus identification and response preparation in a movement task. Indeed, our findings show that in this frequency band the ERD/S representation during observation has similarities with the muscle representation during execution. In particular, we found stronger similarities during the holding phase of the movement, which indicates that when visually processing
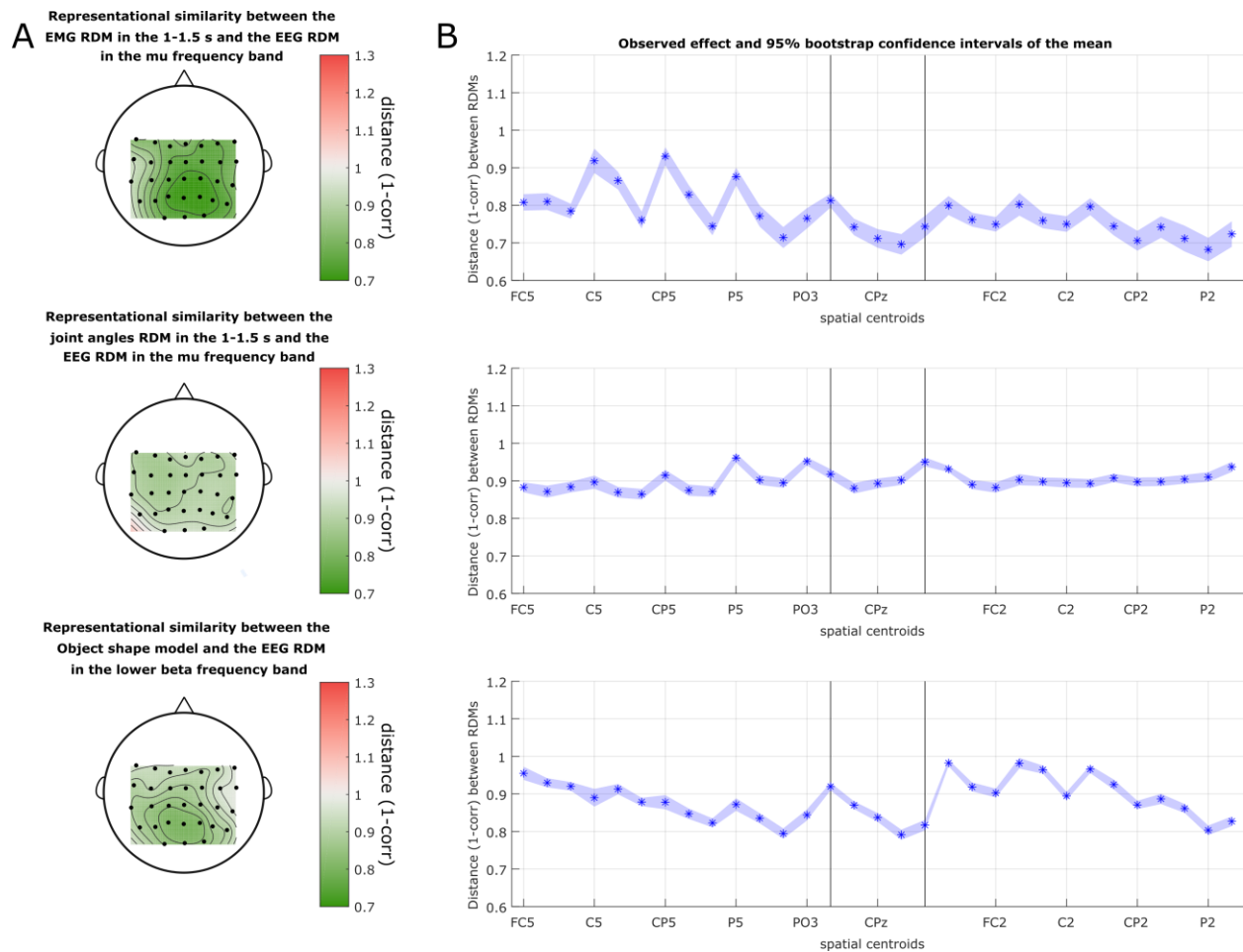
Figure 3. (A). Topographical RSA in the specified frequency bands. On the top, the dissimilarity w.r.t. the EMG representation in the time window between 1–1.5 s. The middle topographical plot shows the dissimilarity w.r.t. the joint angles representation in the time window 1–1.5 s. The bottom topographical plot shows the dissimilarity w.r.t. the categorical Object shape model. (B) Bootstrapping results of the RSA for the three representations shown on the left (A) panel. Centro-parietal and occipital brain regions show smaller distances (higher correlations) between the reference (EEG) representation and the candidate (behavioral EMG - top left and categorical Object shape – top right) representations. The shaded area indicates the 95% confidence interval computed after 500 bootstrapping iterations.

the hand-object grasping interaction, we focus on the final grasping posture.

As we have already observed before in [20], the kinematic representations based on joint angles were similar to the EMG representations; however, the similarity between the kinematic representation and the EEG representation during the observation period was lower, indicating that the kinematic representations may contain additional grasping information that is not encoded in the EEG brain patterns related with visual processing or motor planning.

Concerning the categorical models, we found that the model describing the type of grasp is the least correlated with the EEG representation during the observation of grasping hand postures, the model describing the thumb position during grasping movements showed slight similarities with the EEG representation during observation on central and ipsilateral regions in the low beta frequencies. Furthermore, the model based on the object's shape showed the largest similarities (smallest distances) to the EEG representation during the observation period.

These similarities were found in occipital areas in the low beta frequency range. The large similarities in both mu and beta bands with the Object shape model indicate that during the observation phase there are neural processes related with visual processing (potentially due to a sequential search [34]) as well as motor planning or imagination of movement.

CONCLUSION

To sum up, our findings indicate that the neural representation of observing images of hand-object grasping interactions shares similarities with the muscle representation during the grasping posture holding phase as well as with the model that encodes the information about intrinsic properties of the object, such as shape and size. These findings are of particular relevance for the control of neuroprostheses based on EEG signals and shed some light on the joint relation between neural processes such as planning or imagination (inevitable when observing a hand-object interaction) and the actual behavioral representations

associated with grasping execution.

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