Planning functional grasps of tools vs. non-tools:
decoding conditions from brain activity

Mikołaj Buchwald[1], Łukasz Przybylski[2], Gregory Króliczak[2]

[1] Cognitive Science Program, Institute of Psychology, Action & Cognition Laboratory, Adam Mickiewicz University in Poznań, Poland

[2] Institute of Psychology, Action & Cognition Laboratory, Adam Mickiewicz University in Poznań, Poland

INTRODUCTION

Planning functional actions with tools is associated with activity within a left-lateralized **praxis representation network** (PRN) [1]. It is hypothesized that its node in the **Inferior Parietal Lobule** (IPL), specifically, the anterior division of the left Supramarginal Gyrus (SMG), is critical for integrating semantic and conceptual inputs into such actions. These inputs may come primarily from the caudal Middle Temporal Gyrus (cMTG), an area which also seems to play an important role in planning functional grasps of tools [2].

Previous research has shown that **Multi-Voxel Pattern Analysis** (MVPA) can be applied to decoding motor object-directed and actions-related brain activity patterns [3,4]. These studies have focused on differentiating between functional states of the brain.

Here we examined whether MVPA can be used to predict IPL activity associated with planning **functional grasps of tools**. Our goal was to predict whether participants planned to grasp a tool with an associated function or a non-functional control object.

METHODS

Participants
Scans were acquired from **20 right-handed participants** (age range: 19-24, mean age: 22.7, 10 woman; mean Laterality Index: 92.9).

Design and stimuli
Each experiment consisted of **5 functional runs**, 24 trials each, 12 tools and 12 non-tools (shown in Fig. 1 below). Participants planned functionally appropriate grasps of tools or simple grasps of non-tool objects whose handles were matched for size and/or complexity. Then, pantomimed grasp execution was performed. The planning phase involved a 1.5-s presentation of a target stimulus, and a variable length (1.5, 2.5, or 3.5 s) delay interval (see Fig. 2). Only volumes within the first 3 seconds of the planning phase were included in decoding.

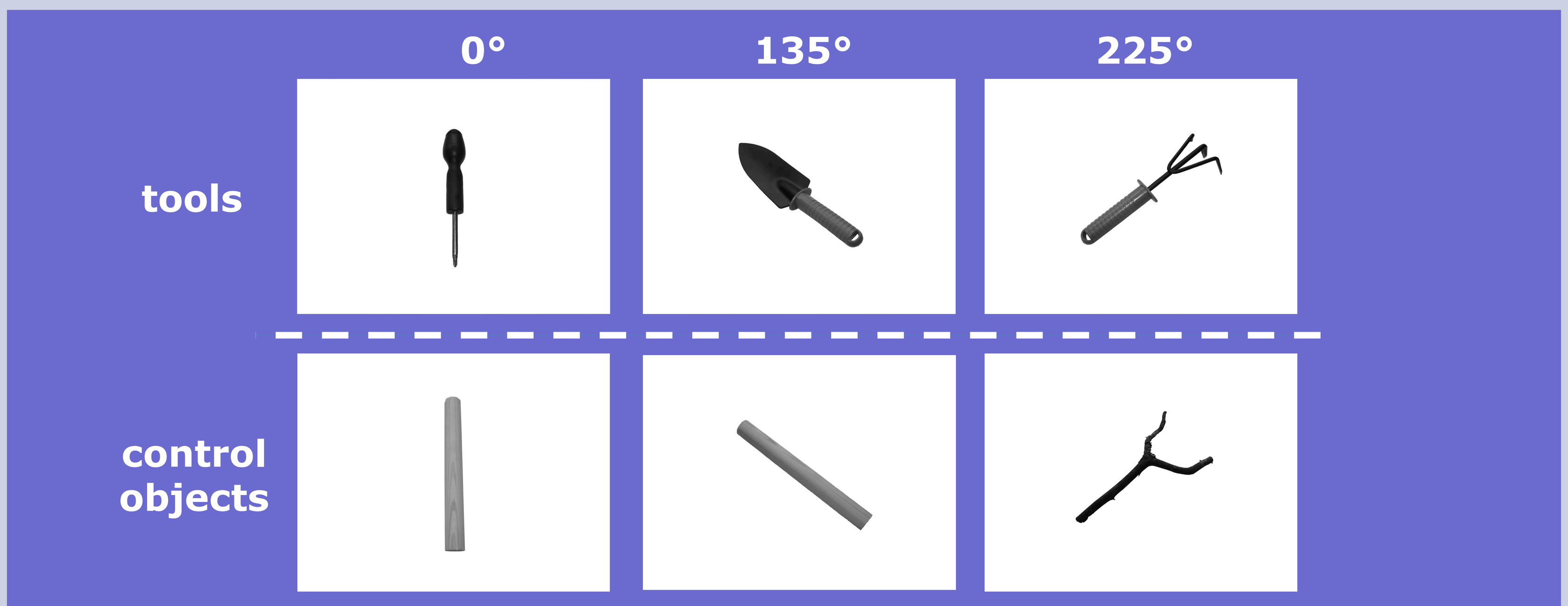


Figure 1: Examples of stimuli used in the experiment. The stimuli were high resolution pictures of 12 tools and 12 non-tools. The objects were presented in three different orientations (0, 135, and 225 degrees).

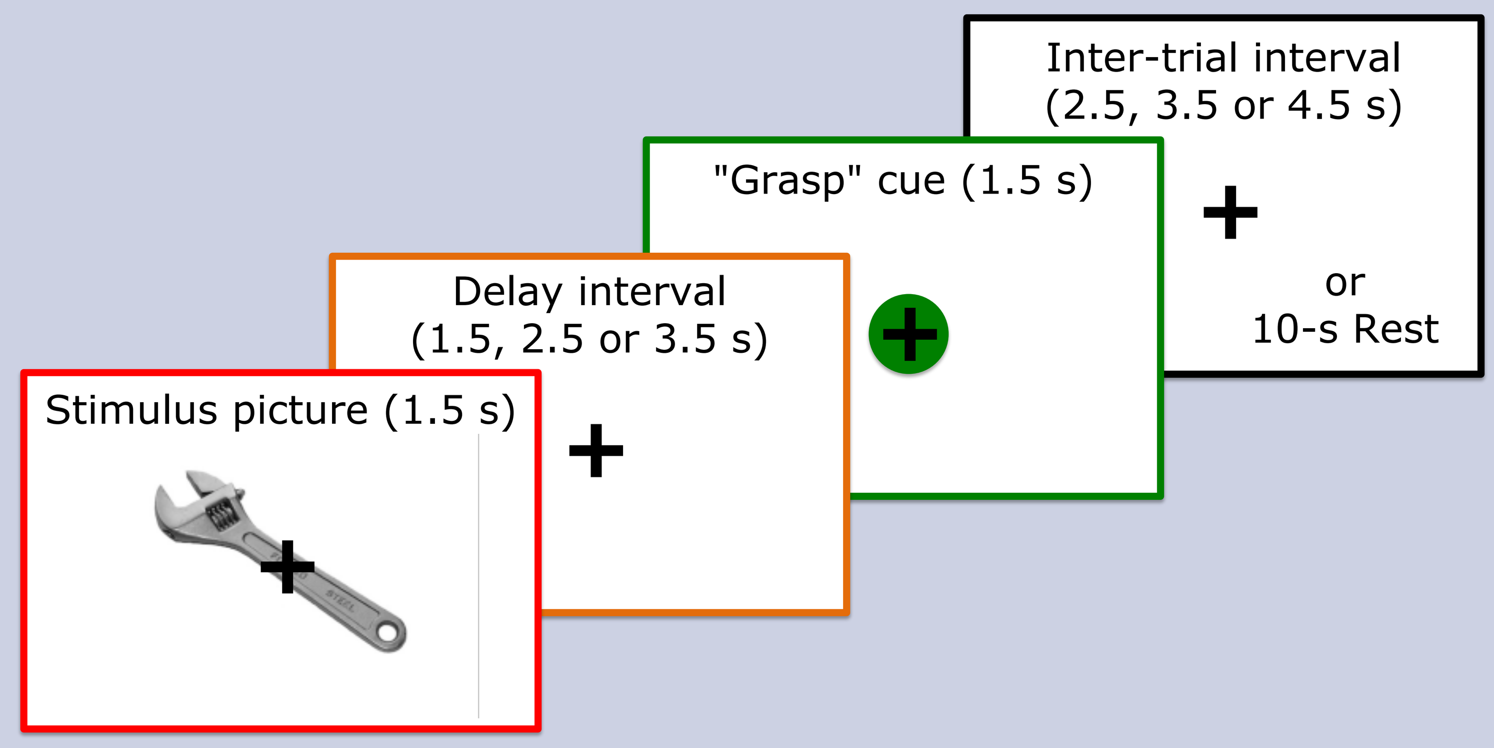


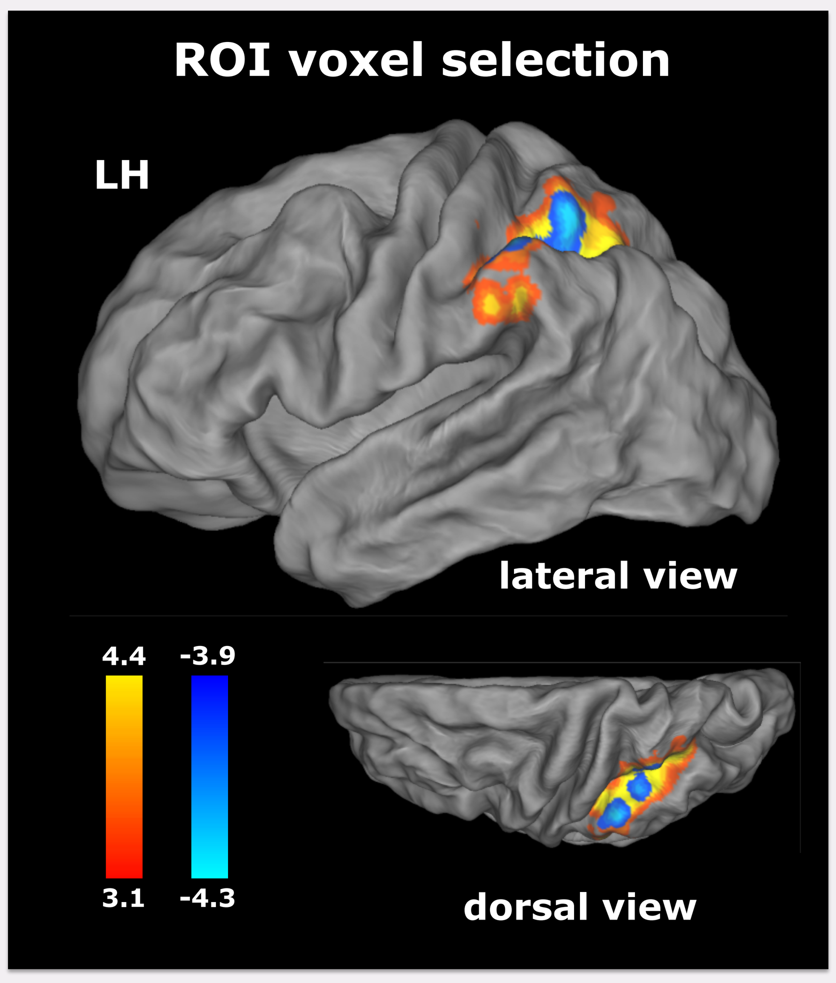
Figure 2: Trial structure and timing. The 1.5-s **Stimulus** picture was followed by a variable (1.5, 2.5, or 3.5 s) **Delay interval** for grasp planning, and a 1.5-s **"Go"** cue for the execution of the pre-planned grasp. **ITIs** were 2.5, 3.5, or 4.5 s. Additional Rest intervals were introduced pseudo-randomly and their duration was 10 s.

Imaging parameters
Siemens's **3T** TRIO MRI Unit (equipped with 32 channel head coil) in the Laboratory of Brain Imaging at the Nencki Institute in Warsaw was used to acquire fMRI (BOLD) echo-planar images (**T2*-weighted**), 35 contiguous axial slices with 3.1-mm isotropic voxels, repetition time (**TR**) = **2000 ms**.

Image analyses
The data were preprocessed with **FSL** FEAT v6.0: motion correction and brain extraction, no spatial smoothing. From the ROI masks (transformed from standard space into subject's native space with FLIRT) **49** highest-value **voxels** were selected. These values were then used to train and test (*k*-fold cross validation, where *k* is the number of runs) three-layer **feedforward neural network** implemented in Python's **theano** module [5,6].

RESULTS

Figure 3: ROI voxel selection example. ROIs were spatially registered to individual subjects' native spaces. Then from the resulting mask **49 voxels** with the highest values were selected for further analyses. In this figure, an example of such a selection is presented (again transformed to standard space for the presentational purposes). Red-yellow scale applies to the original **IPS/IPL** mask from [1], blue - light blue (negative scale) represents 49 voxels with the highest statistic values.



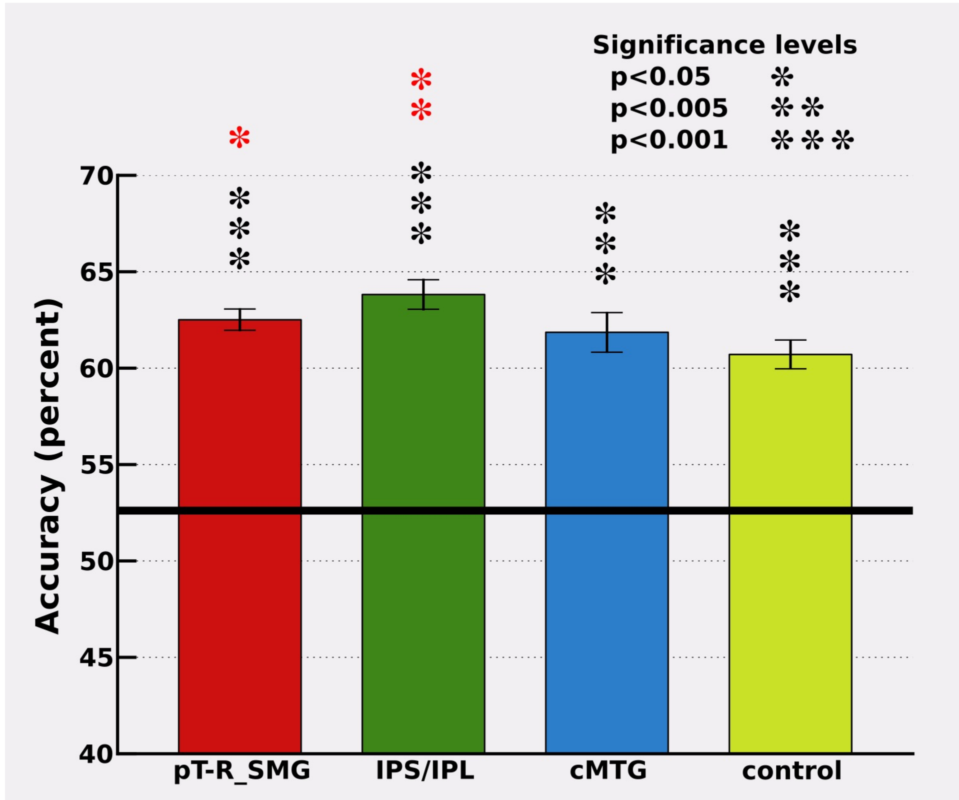


Figure 4: Average MVPA classification accuracies for four distinct ROIs. The means were tested for statistical differences with **one sample t tests**. Black asterisks indicate significant statistical differences from prior chance level (52.61%, indicated by the solid black line). Significance level with respect to the control-region mean score is shown with red asterisks.

Cross-validation results revealed statistically **significant differences** from random chance level in the case of **all four ROIs**. However when compared to the control region (right ventricle) only classification accuracies obtained with SMG and IPS/IPL voxels were significant. The best overall accuracy and statistical significance was achieved for **IPS/IPL** (**62.83 %**). Moreover, when an automatic feature selection method was applied (regardless of ROI) the classification accuracy raised above 74%.

DISCUSSION

Classification level above or near 75% gives quite compelling evidence for the distinctiveness of activity patterns for the planning of functional vs. non-functional grasps, particularly in the posterior parietal lobe. Although not as robust, the prediction of brain states was also quite efficient in the IPS/IPL ROI. This study shows that IPS/IPL can be considered the most crucial node of PRN since activity patterns within this region give substantially more information regarding planning of functional grasps (in contrast with functionless grasps of control objects).

This outcome is consistent with the neuropsychological and neuroimaging studies indicating that left IPL is critical for representing tool-directed actions.

REFERENCES

1. Króliczak, G., & Frey, S. H. (2009). A common network in the left cerebral hemisphere represents planning of tool use pantomimes and familiar intransitive gestures at the hand-independent level. *Cerebral Cortex*, *19*(10), 2396-2410.
2. Przybylski, L., Bidula, S., Pawlak, M., & Kroliczak, G. (05-2014). Neural bases of planning and execution of functional grasps: an fMRI study. Poster presented at the *14th Annual Meeting of the Vision Sciences Society, St. Pete Beach*, FL, USA.
3. Gallivan, J. P., McLean, D. A., Valyear, K. F., Pettypiece, C. E., & Culham, J. C. (2011). Decoding action intentions from preparatory brain activity in human parieto-frontal networks. *The Journal of Neuroscience*, *31*(26), 9599-9610. §
4. Chen, Q., Garcea, F. E., & Mahon, B. Z. (2016). The Representation of Object-Directed Action and Function Knowledge in the Human Brain. *Cerebral Cortex*, 26(4), 1609–1618. http://doi.org/10.1093/cercor/bhu328
5. Team, T. T. D., Al-Rfou, R., Alain, G., Almahairi, A., Angermueller, C., Bahdanau, D., ... & Belopolsky, A. (2016). Theano: A Python framework for fast computation of mathematical expressions. *arXiv preprint arXiv:1605.02688*.
6. Nielsen, M. A. (2015). Neural Networks and Deep Learning. *Determination Press*.

ACKNOWLEDGMENTS

This research was funded by National Science Center (Poland) grant Maestro 2011/02/A/HS6/00174 to Gregory Kroliczak.