Tracking the sub-trial dynamics of cognitive competition

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Abstract

Competition in cognitive processing has lasting consequences for the subsequent accessibility of competing representations. Negative priming (see Fox, 1995 for a review) and retrieval induced forgetting (see Anderson, 2003 for a review) both demonstrate that, when representations compete, the representations that lose the competition are subsequently harder to access. To better understand the competitive dynamics that generate these effects, we developed a method of tracking the activation of the competing representations at the sub-trial time scale. Our methods rely on a pattern classification analysis of EEG data. We found that when a subject views an image, we were significantly above chance at classifying which one (of four) image types the subject is viewing based upon the EEG signal. We show here, the specific time course, within a trial, that we were able to classify over. When the same subject was run in this task twice (on separate days two weeks apart), we were also able to classify the trial types from the second session after training only on data from the first session. Taking advantage of this, we ran the same subjects again, in a second experiment that superimposed images from different categories (e.g. a face over a house) and asked subjects to attend to one of the images. To manipulate the amount of competition on each trial, we adjusted the visibility of the unattended image. We then applied the classifiers trained during the first experiment to the data collected from this experiment. Again, we found that the classifiers were significantly above chance at predicting the class of the attended to image. Additionally, we found that the classifier could also predict the class of the superimposed image. Over increasing levels of competition, we found that the classifier detected increasing amounts of the superimposed image and decreasing amounts of the target image. We report on these analyses.

We are also testing for connections between how much the to-be-ignored stimulus is processed (as detected by the classifiers) and how fluidly it is processed in the future. We hypothesize, based upon negative priming and retrieval induced forgetting effects, that images that are processed more should be subsequently less fluidly processed. We will report on these findings.

Introduction

Making a choice has consequences

- Chosen item is subsequently stronger
- Non-chosen item is subsequently weaker

Examples

- Retrieval Induced Forgetting (Anderson & Neely, 1996)
  - Memories compete to be retrieved
  - Non-retrieved memories are less likely to be retrieved later
- Negative Priming (Tipper, 1985)
  - Visual stimuli compete for attention
  - Non-attended stimuli are slower to be attended to later

In retrieval induced forgetting:

- Non-chosen item must activate to show subsequent weakening

Perhaps the same is true for negative priming

- If we can detect perceptual processing, we could test for this

We will use the Delayed-match-to-sample task

- EEG data from the sample display is response artifact free
- Match response collects reaction time data
- Possible to add distractor to cue or probe
  - * Distractor during cue will suppress the distractor image
  - * Distractors during probe cause interference
  - * Suppressed distractors will cause less interference

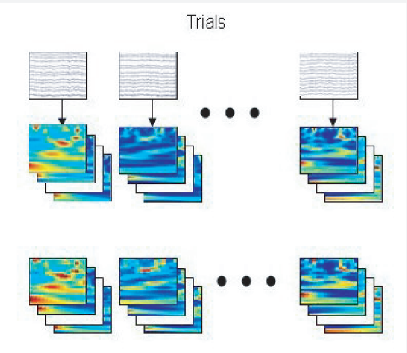
Hypothesis

Distractors that activate during sample displays will cause less interference on probe displays and show faster reaction times.

Decoding EEG via distributed pattern analysis

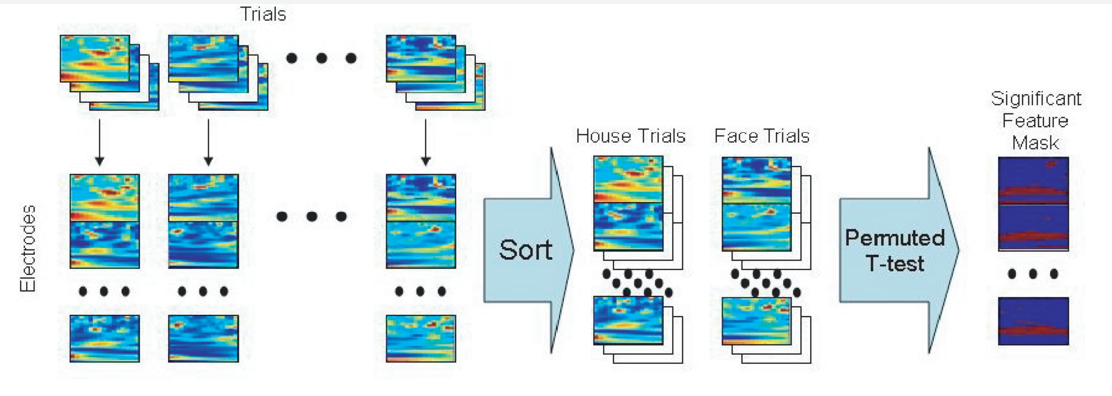
Data preparation -

- Collect data with 79 electrode cap (1000Hz sampling rate)
- Remove trials with excessive noise or blinks
- Perform frequency decomposition
  - Wavelet decompsition (6 cycle Morlet wavelet)
  - 49 frequency bands between 2 & 128Hz
  - Extract power of each frequency band
- Collapse data to form 20ms time bins (averaging)

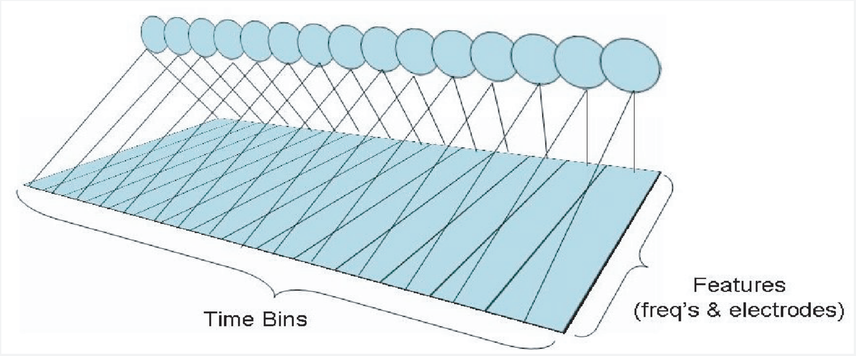


Classification preparation -

- Perform feature selection across *time bins / frequencies / electrodes*
  - Compute non-parametric *p*-value for each combination
  - Include features with $p<0.05$ as an input feature



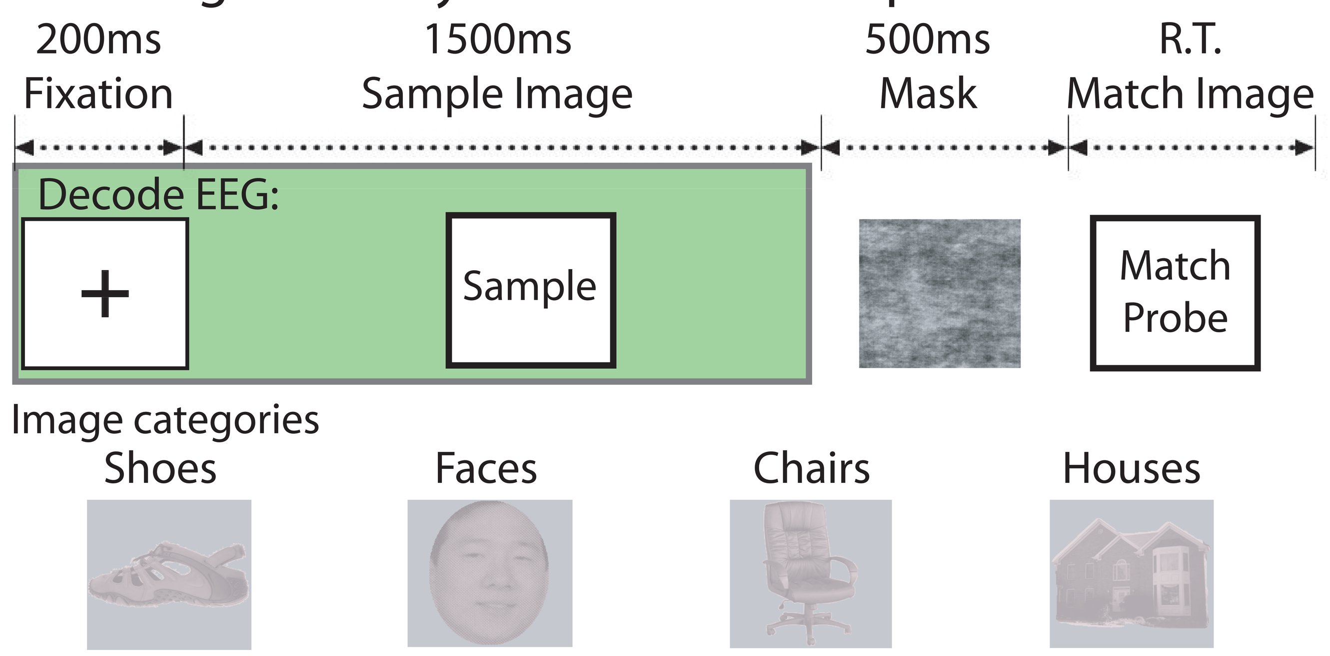
- Build an artificial neural network (ANN) classifier for each time bin
  - Input patterns -
    - Significantly discriminating frequency / electrode combinations
  - Output patterns -
    - Binary regressors



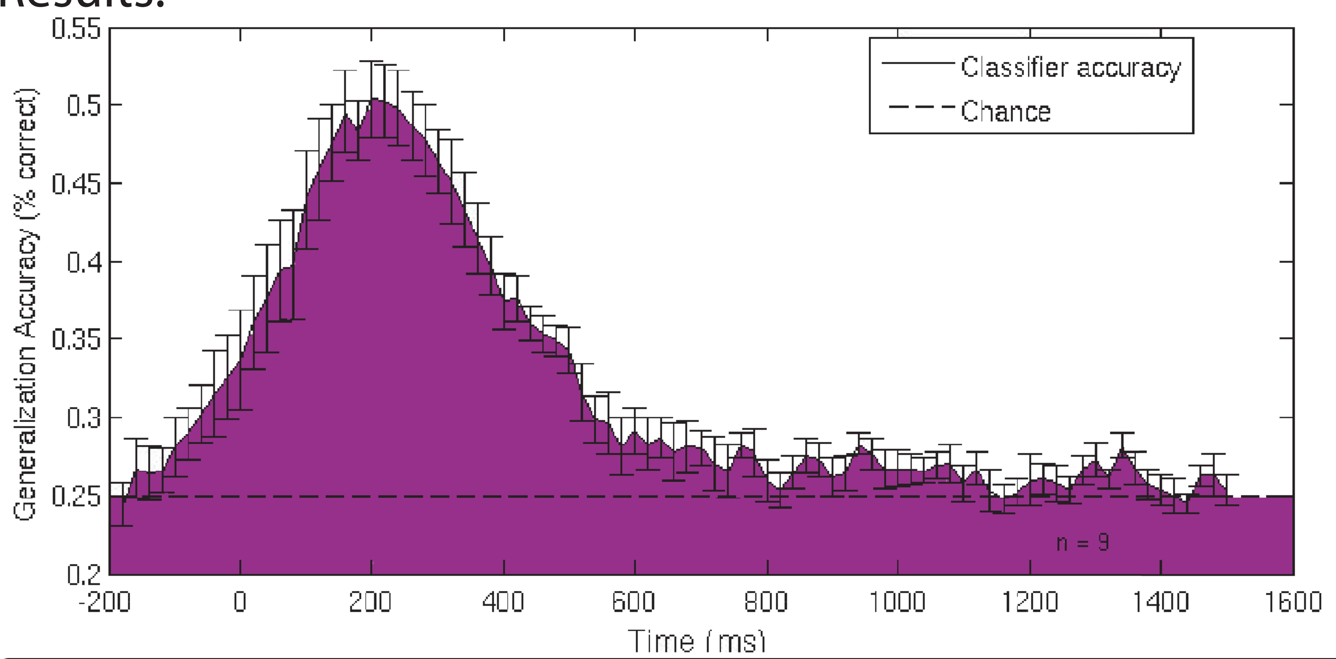
Classification procedure -

- Training the classifiers (for each time bin)
  - Use backpropagation learning algorithm
  - Use N-1 approach validation approach
    - Train on 9/10th of the trials
    - Test on remaining 1/10th
    - Repeat 10x

Task Design 1: Delayed-match-to-sample



Results:



We are able to classify the category of a presented image from the EEG over a transient burst during the first 500ms of the image presentation.

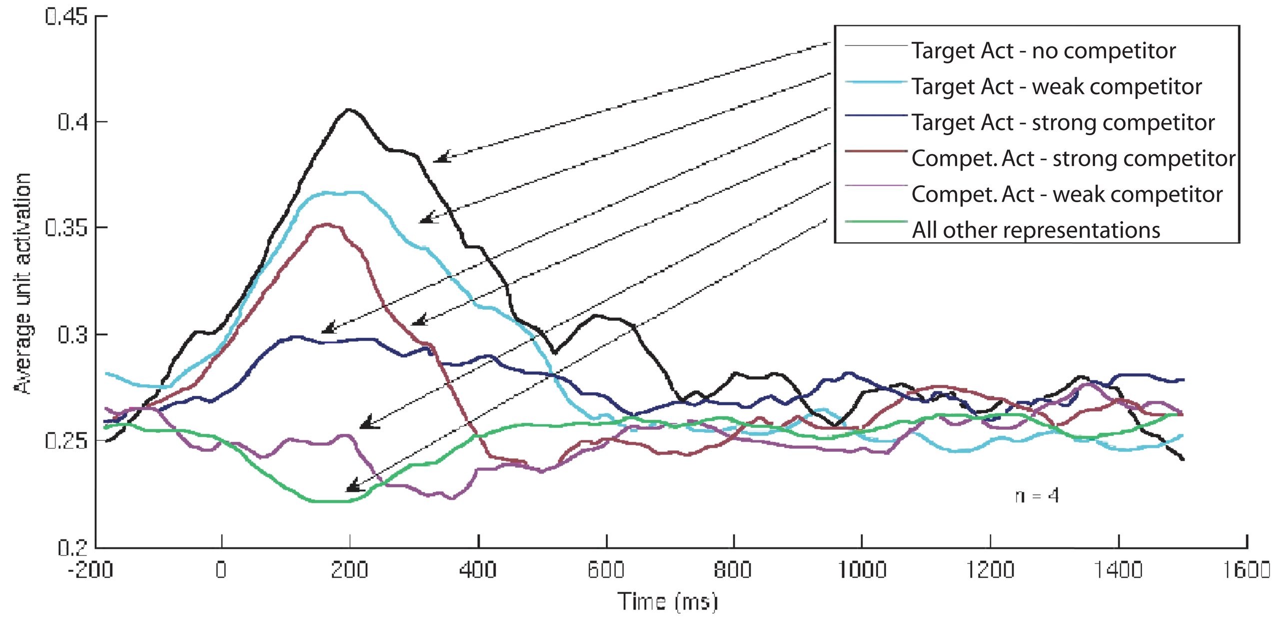
Task Design 2: Delayed-match-to-sample with distractors

Added superimposed image, ask subjects to ignore it

- Sample image tinted red to guide subjects
- Second image is always from a different category
- Three levels of distractor - None / Weak / Strong

E.g.

Results:

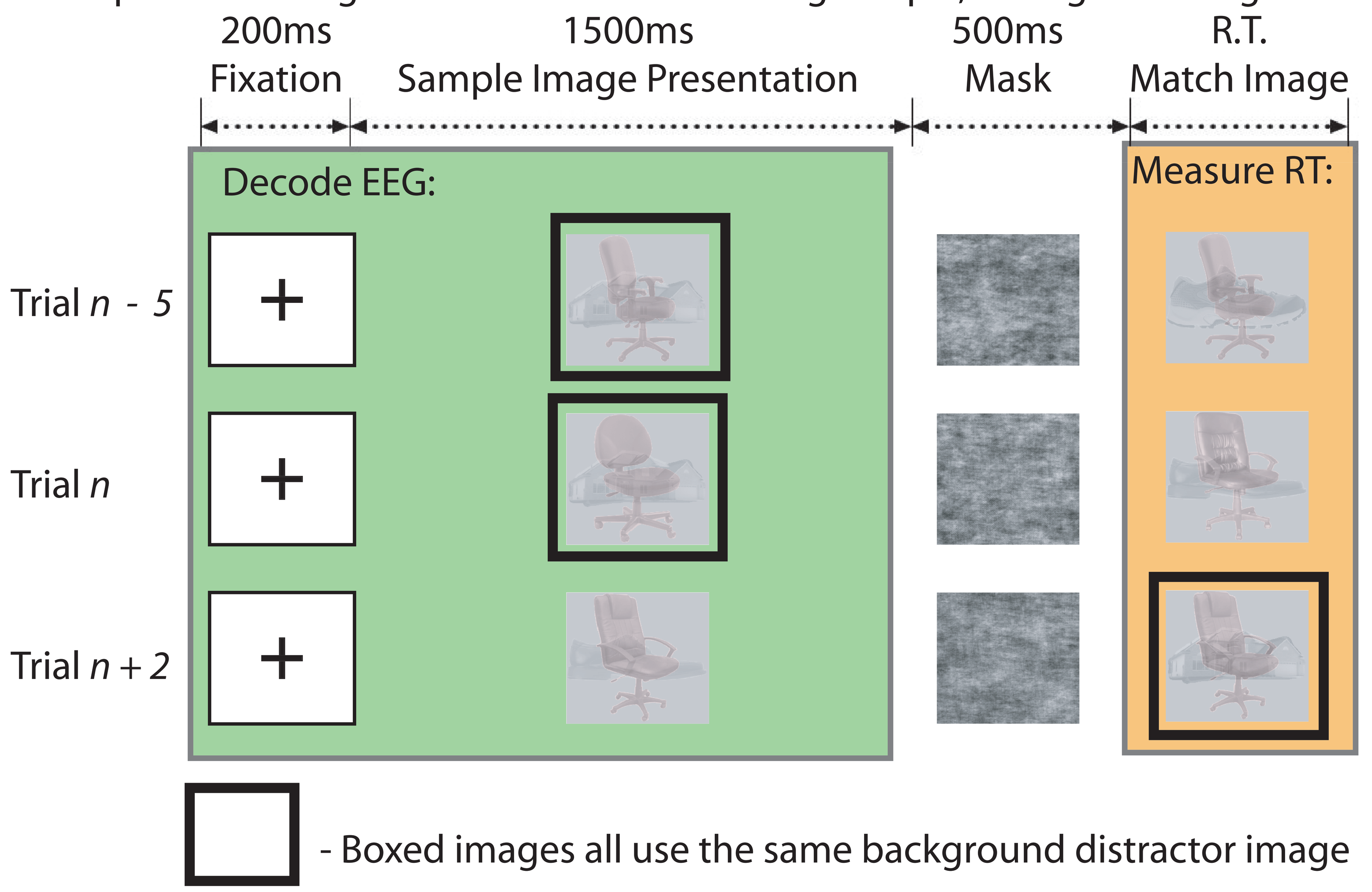


We are able to classify the category of the sample and distractor images

Task Design 3: (Preliminary results only)

Delayed-match-to-sample with cue & probe distractors

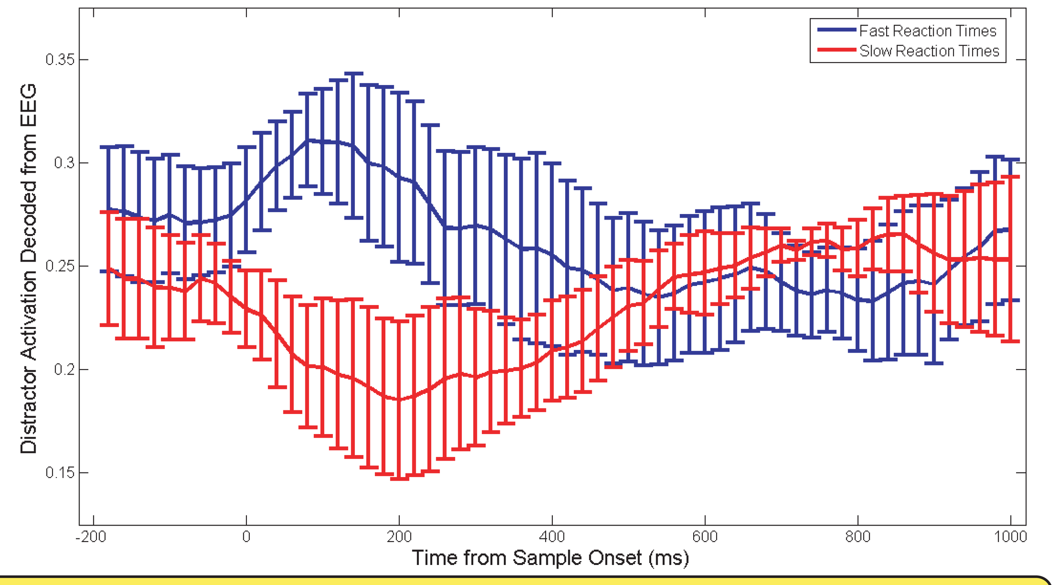
Manipulation Design - Present distractor during sample, and again during match



- Boxed images all use the same background distractor image

Results:

- Split data into fastest 25% of trials & slowest 25% of trials
- Compute average activation of distractor during match images for corresponding fastest and slowest match RT's



These preliminary results indicate that the distractors on the fastest trials had shown greater activation during the preceding sample image displays.

Results & Discussion

It is possible to decode which image category the subject is viewing.
The trained decoders can detect the category of multiple presented images
The strength of the classifier output varies with manipulation of the stimuli.
Preliminary evidence supports the idea that these decoders will be useful to examine difficult to observe dynamics such as distractor activation in a negative priming study.

References:

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Haxby JV, Gobbini MI, Furey ML, Alumit I, Schouten JL & Pietrini P, (2001) Distributed and overlapping representation of faces and objects in ventral temporal cortex. *Science*, 293, 2425-2430.

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