Lifelogging and EEG: Utilising Neural Signals for Sorting Lifelog Image Data

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Introduction & Background

Lifelogging– particularly image capture – is capable of generating vast amounts of image data of complex human activates and events which can be difficult to automatically sort and navigate. In this work we demonstrate how neural signals from EEG (Electroencephalography) can be used to help sort and navigate these datasets at high speed. By using EEG we can detect a variety of attention related neural responses to viewing lifelog images which in turn allows us to sort them from the subjective perspective of which images caught the person's attention most significantly.

EEG signals have been shown to display detectable neural correlates of cognitive processes like image recognition and detection. One set of signals in particular here are ERPs (Event-related Potentials) that can be seen after a stimulus like an image appears on a screen. Most notably, the P300 ERP signal is observed in response to images that capture attention in a significant way for instance when asked to search for particular types of images presented at a high-speed on screen - a strategy known as RSVP (Rapid Serial Visual Presentation).

Although the P300 signal has a stereotyped pattern over the scalp (topography), variations in its amplitude, latency and other topographic features occur in response to different kinds of attentionally-orientating images. By measuring these characteristics we can not only differentiate between target and non-target images but further extend this strategy to identify different types of target images for the user.

Methodology

In this experiment we sought to determine whether images could be sorted by using neurals signal recorded using EEG while the participant viewed their lifelog data. Two participants using an Autographer wearable camera captured 4 days - of approximately 8 hours a day - of image data as they went about their daily activities. Roughly 360 images were captured per hour.

In order to introduce consistent concepts to be searched for later in the experiment, on days 1 and 3 participants engaged in 4 activities: *chess for 15 minutes, checkers for 15 minutes, drawing symbols on a whiteboard for 15 minutes and drawing letters on a whiteboard for 15 minutes.* This was to ensure enough samples of each concept to be searched for would be available for the later part of the experiment where the participants would need to search for two of these concepts but disregard the other two.

Following data collection the two participants were shown their lifelog images in a randomised order while having their EEG recorded. A 32-channel EEG system was used. Images were presented at a rate of 4 Hz and in total 9600 images were presented in 2 blocks of 4800 images each where the second block was randomized again. Prior to the EEG recording session participants had not seen their captured data. At the beginning of the session participants were given two target concepts to search for. Participant 1 searched for images playing chess and instances of writing symbols on the whiteboard. Participant 2 searched for instances of playing checkers and writing letters on the blackboard.

Methodology – Continued

By repeating the first block in the experiment 320 target images, 320 distractor images, and 8960 non-target images in total.

The target categories were intended to have high visual similarity with a distractor category so at first glance they would appear to be a potential target. Participants were instructed to count the number of occurrences of targets per block so as to ensure engagement in the task and so as to validate detection performance afterwards.

Figure 2: Samples images used in experiment. Example of shape drawing, letter drawing, playing checkers, playing chess and 2 non-target images (from left to right, top to bottom).

Analysis and Results

EEG signals following the experiment were bandpassed between .1Hz-20Hz. ICA (Independent component analysis) was used to remove noise. EEG channels were digitally referenced to linked mastoids. A Bayesian ridge classifier was used with a cross validation strategy (C=20, 10% test set) using an ROC-AUC accuracy measure. Weight coefficients used (like shown in plots) were derived for each comparison type using the sum of absolute values of weights for each channel. In addition, AUC was assessed using only single channels to derive a supplementary measure of accuracy for single-channel detection instances.

	Participant 1 (AUC)	Participant 2 (AUC)
Distractors vs. Targets	.70	.66
Targets vs. Distractors	.83	.96
Targets vs. Non-targets	.92	.88
Distractor 1 vs. Distractor 2	.94	.94
Target 1 vs. Target 2	.81	.97

Table 1: Comparison of classification accuracies across 5 comparison types using all channel data.

	Participant 1 (AUC)	Participant 2 (AUC)
Distractors vs. Targets	.70	.63
Targets vs. Distractors	.75	.90
Targets vs. Non-targets	.83	.83
Distractor 1 vs. Distractor 2	.88	.83
Target 1 vs. Target 2	.76	.92

Table 2: Comparison of classification accuracies across 5 comparison types using highest accuracy electrode.

Analysis and Results - Continued

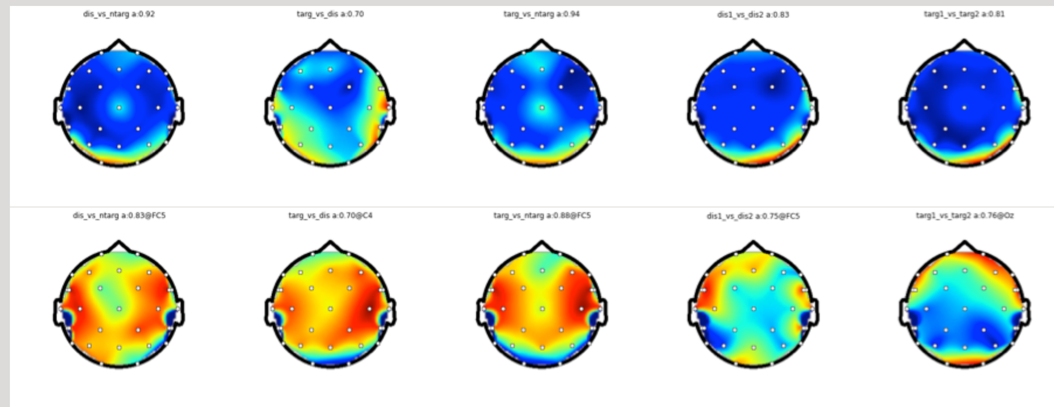

Figure 3: Discriminative topographic weights for participant 1 for comparison types. Top row is comprised of weights derived using all EEG channels and bottom row reflects individual channel AUC accuracies. Topographic plots (from left to right): Distractors vs. Targets, Targets vs. Distractors, Targets vs. Non-targets, Distractor 1 vs. Distractor 2 and Target 1 vs. Target 2.

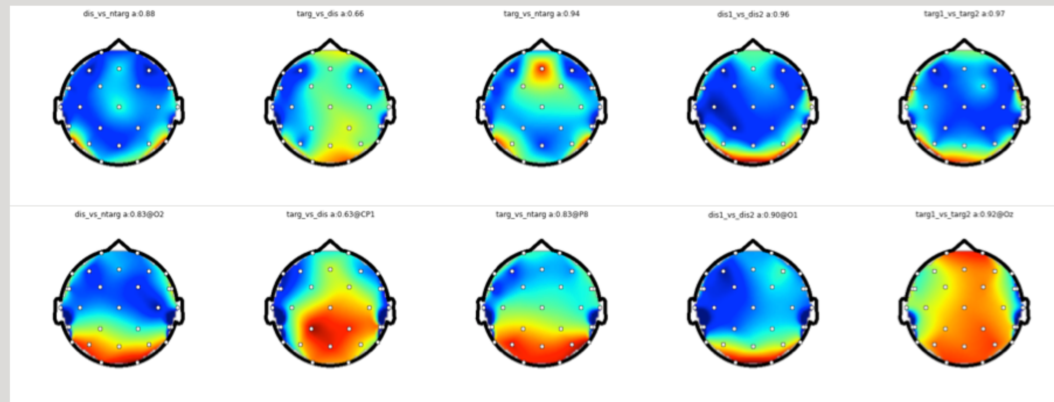

Figure 4: Discriminative topographic weights for participant 2 for comparison types. Top row is comprised of weights derived using all EEG channels and bottom row reflects individual channel AUC accuracies. Topographic plots (from left to right): Distractors vs. Targets, Targets vs. Distractors, Targets vs. Non-targets, Distractor 1 vs. Distractor 2 and Target 1 vs. Target 2.

Conclusions and Discussion

In this work we show it is possible to use neural signals to sort images. The results in table 1 demonstrate that it is not only possible to discriminate targets from non-targets but also to do so for different types of targets and furthermore images which are not targets but share high visual similarity. The results in table 2 further show that this can be done too using single electrode sites on the scalp, an important consideration for when developing for or designing consumer grade devices. Figures 3 and 4 visually show this discriminative information across scalp to help understand how optimal detection sites change depending on the number of electrodes being used and that a number of key electrodes sites are often obstructed by hair – an issue for many consumer grade EEG devices.

This work is a first step towards building systems that can more generally detect and sort a variety of – subjectively defined - concepts in lifelog image sets in a convenient fashion whilst detecting important differences between why attention was captured for certain types of images in the first place. The ultimate aim is to develop systems which can extract a rich set of subjectively defined concepts for images from neural responses.

QS Relevance

While advances have been made in computer vision and related fields in sorting and indexing lifelog image data, a gap exists between what a computer understands to be relevant and what the person deems relevant. Here we propose by using EEG we can move towards bridging this gap by using neural signals related to attention and interest to be able to sort and index these images at high speed. While this is proof-of-concept work, it serves as a starting point to further explore the capability of using such systems to tackle the problems associated with capturing large volumes of lifelog images that require manual annotation.

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