Data-driven detection of memory encoding from EEG in an audiovisual task

Ana Matran-Fernandez [1,*] **and Sebastian Halder** [1]

[1] *Essex Brain-Computer Interfaces and Neural Engineering Lab, School of Computer Science and Electronic Engineering, University of Essex, Colchester, United Kingdom*

Correspondence*:
School of Computer Science and Electronic Engineering, University of Essex,
Wivenhoe Park, CO4 3SQ Colchester, United Kingdom
amatra@essex.ac.uk

SYNOPSIS

Reliably detecting memory encoding can help diagnose memory impairments and provide insights into neural correlates of memory formation from electroencephalogram (EEG). However, there is little prior literature that can be used to drive feature extraction to detect encoding in audiovisual memory tasks. Our objective is to explore the use of an explainable neural network to detect memory encoding from EEG while participants watch videos. We use EEG-ITNet in single- and multi-user scenarios and show that detecting successful memory encoding from EEG data using audiovisual stimuli is possible, particularly when recordings from multiple participants are used to train the models. In the future we will explore the features identified by EEG-ITNet to detect a neural signature of memory encoding. Our framework can also be utilized for data-driven feature discovery in tasks where there is little prior knowledge.

BACKGROUND

Successfully encoding events into episodic memory profoundly impacts our personal lives, education, and career (Tulving, 1983). Detection of memory encoding events in real-time could increase our understanding of why some events are remembered and others are not. This in turn would allow us to improve memory retention, e.g., in educational environments or to support people with a decreased memory capacity. The detection of memory encoding events could be implemented using a brain-computer interface (BCI) if we understand how these events are reflected in neurophysiological signals. Memory encoding has long been investigated from a neurophysiological perspective and appears to be localised in the hippocampus (Sugar and Moser, 2019). Crucially in the context of our work, it appears to be reflected in the electroencephalogram (EEG) (Klimesch et al., 1994). EEG correlates of memory include oscillatory activity (in particular in the theta band), event-related potentials, and connectivity (Werkle-Bergner et al., 2006; Rudoler et al., 2023). How these features combine in a complex audiovisual scenario reflective of real-world environments is unclear, therefore we decided on a data-driven approach utilising an explainable neural network (Salami et al., 2022). Here we present an initial attempt at detecting memory encoding events from single-trial EEG while participants viewed complex audiovisual stimuli.

METHODS

Experiment

Protocol

Following Sweeney et al. (2022), the experiment comprised two phases.

In the encoding phase, EEG data were recorded while participants watched 1,000 videos (equal number of high- and low-memorable videos) in random order (1 second fixation cross between videos) from the Memento10k dataset (Newman et al., 2020).

Twenty-four to 72 hours after the recording, participants provided memorability annotations for 2,000 videos (the ones shown during the EEG recording + a random 1,000 from Memento10k). Participants were required to categorise each video into “remembered” or “not remembered”.

Data acquisition and preprocessing

We collected data from 40 participants (32 males, 8 females; 2 left-handed), aged 22–65 (mean age = 30) who had normal or corrected-to-normal vision.

EEG data were acquired with BioSemi ActiveTwo system (64 electrodes, 2048 Hz sampling rate). Bad channels were interpolated offline, and data were common average referenced, band-pass filtered between 0.1–30 Hz with a zero-phase Butterworth filter, and downsampled to 128 Hz using *MNE* (Gramfort et al., 2013). Ocular artifacts were removed via independent component analysis.

For classification, we extracted 4.5-s long epochs beginning 1 second before clip onset (baseline 250 ms to 0 ms, rejection threshold 70 μV).

Exclusion criteria

We excluded participants who: did not perform the online annotation (1/40); had technical difficulties (6/40); above 30% false positive rate in the online annotation (15/40); or excessively noisy recordings (6/40). The final dataset comprised 12 participants (9 males, 3 females; all right-handed), aged 22–34 (mean age = 28).

Detection of memory encoding

EEG-ITNet

We used EEG-ITNet (Salami et al., 2022), an explainable temporal convolutional neural network, to discriminate between successful/unsuccessful encoding in two scenarios. Training parameters for each case are given in Table 1. The network was trained using Adam optimizer with default parameters.

Single-user prediction

The EEG recordings of each participant were independently used to train and evaluate EEG-ITNet models. Epochs from each participant were first divided into a stratified training and test set. The test set comprised 20% of the epochs from that participant. The training set was further split using stratified 10-fold into training and validation sets to evaluate the performance of EEG-ITNet and to allow for early stopping. In each fold, the data were standardised.

For early stopping in the final model, epochs from the participant’s training set were randomly divided into 80% for training and 20% for validation.

Table 1. Training parameters for EEG-ITNet for each scenario. Epochs were rebalanced for training by downsampling the majority class, but AUCs on the validation and test sets are calculated on the imbalanced data sets. Dropout rates were taken for each scenario from Salami et al. (2022). To avoid overfitting, the training process was stopped early by monitoring the validation loss if no improvements were obtained within '*patience*' epochs.

Scenario	Dropout rate	Batch size	Number of epochs	Patience
Single-user	0.4	256	3000	250
Multi-user	0.2	256	1500	250

Multi-user prediction

In this scenario, the epochs from all participants were combined to train EEG-ITNet. Individual participant data were first standardised. We used a stratified random 80/20 train/test split to ensure that the percentages of epochs from both classes were maintained across splits. For cross-validation, the training set was divided using stratified 10-fold cross-validation.

For early stopping in the final model, 20% of the training dataset was used as a validation set to monitor the performance of the model during training.

RESULTS

Single-user prediction

Figure 1(left) shows the cross-validation performance for single-user memory encoding detection. The average value of Area Under the receiving operating characteristic Curve (AUC) across all participants was 0.61 ± 0.06, which is above random performance. Performance on the test sets was lower, at AUC=0.51 ± 0.12, showing that the models are overfitting for some participants (perhaps due to the limited dataset size compared to the number of parameters of EEG-ITNet). However, for 7/12 subjects, AUCs on the test set were above chance level, showing that EEG-ITNet can be used to detect encoding of memories in single trials.

Multi-user prediction

Performance of EEG-ITNet on cross-validation was AUC=0.68 ± 0.04 for the multi-user scenario (see Figure 1(right)). A one-sided Mann-Whitney U test confirmed that the model is significantly better than random chance ($U = 0.0$, $p = 9 \times 10^{-5}$). The performance on the test set was AUC=0.67, on par with cross-validation results, showing that the multi-user scenario generalises better than the single-user.

DISCUSSION

We used EEG-ITNet to discover neural correlates of memory encoding in a data-driven approach. Our results show that it is possible to discriminate between successful/unsuccessful long-term memory encoding. In the future we will expand this work on two fronts. First, by exploring the features extracted by EEG-ITNet to identify transferable neural correlates of memory encoding (Salami et al., 2022). Secondly, by creating fine-tuning and leave-one-out scenarios to assess the performance of our models on new users with little/no training respectively—which might be desirable in many applications (Kunjan et al., 2021; Lemoine et al., 2023), such as diagnosis of memory impairments.

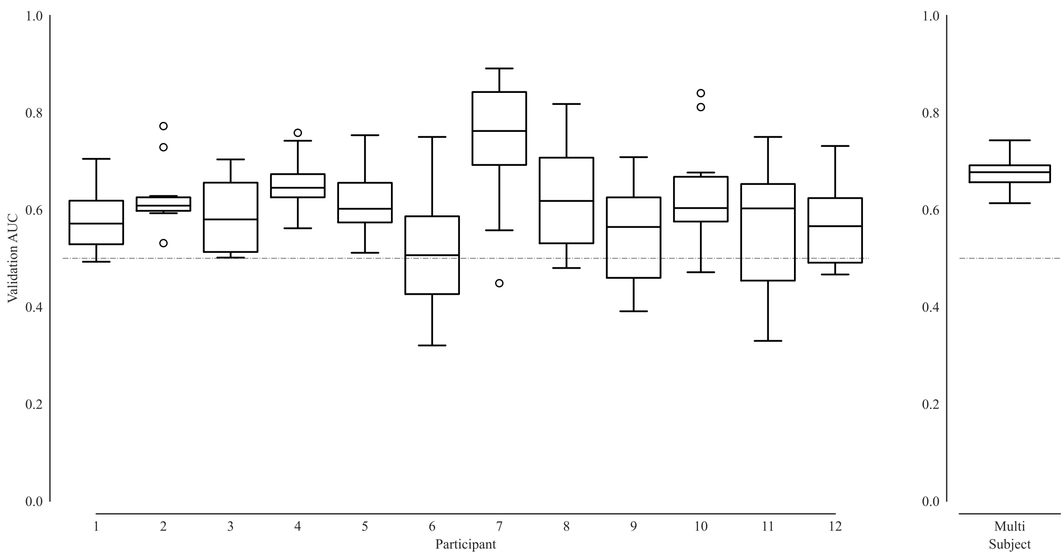

Figure 1. Boxplots of AUCs across 10-fold stratified cross-validation for each participant in the single-user scenario (left) and across all folds in the multi-user scenario (right). The horizontal line at AUC=0.5 shows the level for random performance.

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