Proceedings of the 6th International Brain-Computer Interface Conference 2014 DOI:10.3217/978-3-85125-378-8-17

# Towards a passive brain computer interface for improving memory

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**Abstract**

We propose a passive BCI system based on our previous results on deciphering neural correlates of memory from single-trial EEG. Our system will measure the brain activity of a user, and infer the user's preparedness for learning to present study items at estimated optimal times. The system will also monitor the brain activity during learning/encoding to assess whether the encoding process was successful or not. These studied item will be presented in the future with an appropriate lag depending on the predicted level of encoding to strengthen retention. The system will also extract information related to the user's confidence during re-presentation of the item to assess the level of reinstatement. Items with low reinstatement will be presented again to ensure encoding. Spacing models can be incorporated with the system to determine these lags for optimal retention. Other systems that monitor

## 1 Introduction

Faced with rising classroom sizes and the higher incidence of learning difficulties, such as ADD, we need a tool that can improve a user's ability to remember study material. Such a tool may also be useful for addressing age-related memory decline. We propose a system that tailors instruction to each individual's brain dynamics. The system will use neural activity reflecting memory encoding and retrieval to choose optimal presentation times and intervals to improve memory. This system can be considered a passive BCI where the system monitors the brain in real-time to extract information related to memory encoding/retrieval.

## 2 Types of memory related neural processes

We review findings on the neural correlates of long-term memory which can be used for an EEG-based passive BCI system and give a summary of the classification results applied to single-trial EEG data to identify neural signatures reflecting memory encoding and retrieval.

### 2.1 Encoding Success

There are significant differences in the spectral and temporal patterns between remembered and forgotten trials during study item presentation which are known as subsequent memory effects (SMEs). The difference in event-related potential (ERP) between subsequently remembered and forgotten items is also known as the Dm (or difference due to memory) effect [13, 12]. It is observed around 400 to 800ms after study item presentation. Brain oscillations during encoding

 DOI:10.3217/978-3-85125-378-8-17

also distinguish between subsequently remembered and forgotten items (see [6] for a review). Power decreases for the remembered items typically occur in the alpha (7-12 Hz) and low beta (12-19 Hz) bands [7, 5] of the EEG signal.

We used single-trial classification to successfully distinguish between remembered and forgotten pictures using the temporal and spectral information in the EEG during stimulus presentation [10]. By combining the information from multiple time windows, the *encoding success classifiers* achieved an overall accuracy of 58 % across all 18 subjects. The classifiers gave accuracies significantly over chance ($p < 0.05$) for 9 subjects [9].

### 2.2 Encoding preparedness

EEG, MEG, and ECoG studies have shown that spectral differences in brain activity immediately preceding study item presentation also show significantly different patterns for the subsequently remembered and forgotten trials. This difference is observed in multiple frequency bands ranging from theta (4-7 Hz) [4] to the high beta (19-30 Hz) [3] bands.

These good/bad (for subsequent memory retention) brain states were successfully identified from the spectral information in the EEG signal between -300 to 0 ms before stimulus presentation of pictures in [10]. The classifier combined information from 9 overlapping subbands of the EEG signal (4-7, 6-10, 7-12, 10-15, 12-19, 15-25, 19-30, 25-35, and 30-40 Hz). The overall classification accuracy of the *encoding preparedness classifiers* across 18 subjects was 57.2 % where 9 subjects showed significantly over chance results.

Because study items were presented at a fixed interval without awareness of the subjects' brain state, we used the 10 % of presentations with the highest and lowest classifier confidence as analogs for the best and worst sets in a real-time system. The rate of remembered items gave a 50 % improvement when the study items were presented at the best times compared to the worst (59.6 % items remembered during *good* brain states vs. 40 % during *bad* brain states). For the 10 subjects with the highest overall classification accuracy, the rate of remembered items was a 74 % improvement when the study items were presented at the best times compared to the worst (63.4 % items remembered during *good* brain states vs. 36.5 % during *bad*).

### 2.3 Confidence at retrieval

The parietal ERP old/new effect is the difference in ERP between correctly rejected new and correctly detected old trials during memory retrieval. The old trials show a positive-going deflection compared to the new trials in the left parietal channels between 500-800 ms after stimulus presentation [14]. The frontal ERP old/new effect also distinguishes between correctly rejected new and correctly detected old trials. The ERPs show a more negative peak for less familiar trials in the frontal channels between 300-500 ms after stimulus presentation [2].

We used the EEG data during the recognition phase of a memory experiment and found that it is possible to distinguish unsuccessfully from successfully retrieved studied items with 58.4% accuracy [11] where 20 out of 34 subjects gave significantly over chance results. The likelihood of remembering a study item for trials with the 10 % highest and lowest classifier outputs were 0.8 and 0.45 respectively suggesting that the *confidence at retrieval classifier* outputs reflect the level of retrieval strength during the test phase.

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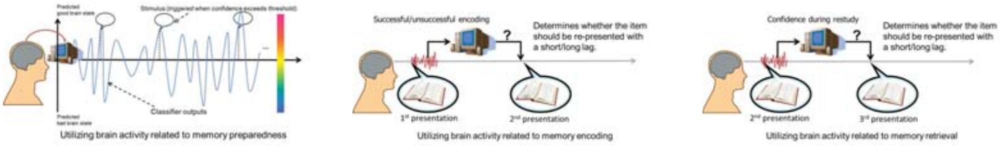


(a) The system monitors the user's brain state in real-time to identify *good* brain states for memory encoding. Study items are presented at these *good* brain states.

(b) The system monitors EEG during initial encoding of a study item. The output of the classifier determines whether the item should be re-represented in the future with a short or a long lag.

(c) The system monitors EEG while a item is restudied. The output of the classifier determines whether the item should be re-represented in the future (for further restudy) with a short or a long lag.

Figure 1: The three components of the proposed system

# 3 A system for improving memory

The three classifiers above (*encoding preparedness, encoding success, confidence at retrieval*) can be incorporated into a passive BCI system to assist users in improving memory. A common real-world learning task is paired-associate learning (e.g. word-meaning lists for students or vocabulary learning for a second language). In this section, we propose a system that incorporates the above classifiers to improve paired-associate learning. The system will present study items to the users following a continuous recognition paradigm where there is no distinction between study and test phases. Items may occur multiple times in the list for restudy.

The *encoding preparedness classifier* monitors the user's brain state in real-time to identify optimal brain states for study item presentation. When the system identifies a near-optimal time for presentation, it gives a scheduled study item (e.g. a target word in a foreign language) to the user. The user responds with either *New* for items they have not seen before, *Don't know* for items for which they do not remember the associations, or with their guess for the previously given association (e.g. the same word in English). After the response, the user receives feedback from the system with the correct association pair. When the user is finished studying/restudying the given association, the next target item appears on the screen at the next detected near-optimal time. With a first-time user, the classifiers can be initialized using training data from other users or the study items can be given at fixed time points. These initial classifiers can be *adapted* to the user in an online manner at the second (*test*) presentation of each item (when the behavioral results are obtained) with the stored EEG data from memory encoding/retrieval.

For a new study item, the lag for re-presentation is determined by the *encoding success classifier*. If the likelihood of encoding success is high (low) for a given item , the item may be re-presented with a long (short) lag. For a restudy item, the lag for re-presentation (for further restudy) is determined by the subject's response and the *confidence at retrieval classifier* output. Incorrect user responses will be re-presented with a short lag; for correct responses, the *confidence at retrieval classifier* output will determine the lag duration. Spacing models can also be incorporated to specifically determine these lags for optimal retention [1].

One disadvantage of the proposed system is that the throughput (rate of learned material presentation) may be lower than a conventional tutoring system due to the waiting period for good brain states. We can overcome this issue by using the good brain states to present the most critical or difficult[1] items. At intervening times, the remaining study material can be

[1] Difficult items may be identified from average hit rates from multiple users or based on previous behavioral/classification results for the specific user.

given to the user with a typical presentation rate [8]. As a long-term goal, we plan to explore the effects of long term use of our system. We hypothesize that the implicit neurofeedback users would get from being presented study items only when they are ready could help them remain in a receptive brain state more often.

# 4 Conclusion

In this paper, we proposed a passive BCI system for assisting memory formation and retention. Our system has three components: 1) it will infer the user's preparedness for learning to present study items at estimated optimal times; 2) it will monitor the brain activity during learning/encoding to assess whether the encoding process was successful or not; 3) it will also extract information related to the user's confidence during re-presentation of the item to assess the level of reinstatement. The incorporation of spacing models was also discussed to specifically determine these lags for optimal retention. Other systems that monitor study performance or user state could also be integrated with the proposed system.

This research was funded by NSF grants CBET-0756828, SBE-0542013 and SMA-1041755, NIH Grant MH64812, and a KIBM Innovative Research Grant.

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