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A System based on 3D and 2D Educational Contents for True and False Memory Prediction using EEG Signals

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Abstract— **Electroencephalography (EEG) has been widely adopted for investigating brain behavior in different cognitive tasks e.g. learning and memory. In this paper, we propose a pattern recognition system for discriminating the true and false memories in case of short-term memory (STM) for 3D and 2D educational contents by analyzing EEG signals. The EEG signals are converted to scalp-maps (topomaps) and city-block distance is applied to reduce the redundancy and select the most discriminative topomaps. Finally, statistical features are extracted from selected topomaps and passed to Support Vector Machine (SVM) to predict brain states corresponding to true and false memories. A sample of thirty four healthy subjects participated in the experiments, which consist of two tasks: learning and memory recall. In the learning task, half of the participants watched 2D educational contents and half of them watched the same contents in 3D mode. After 30 minutes of retention, they were asked to perform memory recall task, in which EEG signals were recorded. The classification accuracy of 97.5% was achieved for 3D as compared to 96.5% for 2D. The statistical analysis of the results suggest that there is no significant difference between 2D and 3D educational contents on STM in terms of true and false memory assessment.**

I. INTRODUCTION

Learning and Memory are two related mental processes; they are both intensively studied subjects in neurosciences [1]. Learning is the change in behavior because of an experience; while memory is the ability to store and recall learned experience [4]. Revealing the learning and memory mechanism of human brain is the core objective of the intelligent science [3]. In cognitive psychology, human memory processes are functionally divided into three categories namely encoding, retention, and recalling [8]. Many models classified the memory into three types, sensory, short-term and long-term memory [3].

The advent of 3D technology and devices has opened the question whether 3D educational contents are more effective than 2D contents for learning and memory recall. In this context, another question is whether we can distinguish true memory from false memory. Addressing this issue, we propose a pattern recognition system that uses EEG brain signals [2] to distinguish true memory from false memory in case of STM for 2D and 3D educational contents.

For assessing true memory and false memory, multiple choice questions (MCQs) can be asked from a subject, but only the answers of MCQs might not give true insight into true and false memories because the answers of some MCQs might be based on mere guess. It is intuitive that the brain states while answering based on guess and learned information will not be same. As such, we use EEG signals, which directly measure the brain states, for the prediction of true and false memories.

The proposed system is a pattern recognition system, which involves feature extraction and classification stages. We learn the system using features extracted from the EEG signals corresponding to correct and incorrect answers and then predict the answers of MCQs to assess true and false memories. If the predicted answer is correct, then it means true memory, otherwise it is false memory. To extract features, EEG signals are converted into topomaps, and redundant topomaps are removed using city-block distance. A novel approach has been proposed for feature extraction from topomaps and Support vector machines (SVM) is used for classification. The mean prediction accuracy of the system is 96.5% in case of 2D and 97.5% in case of 3D. Statistical analysis of the results indicates that there is no significant difference between 2D and 3D educational content on STM in terms of true and false memory.

The rest of the paper is organized as follows: The proposed methodology is discussed in detail in Section II. Section III presents the results and discusses them. Section IV concludes the paper.

II. METHODOLOGY

First we present the detail of the data collection procedure and then discuss different components of the proposed system for predicting true and false memories. The schematic diagram of the system is shown in Figure 1.

A. Data Collection

The steps performed to collect EEG data are given in detail in this section.

Participants & Ethics Approval: Thirty-four healthy volunteers (age range 18-30 years) participated in the experiments. They had normal or corrected to normal vision and were free from any neurological disorders that may affect the experimental results. All the participants signed informed consent document prior to start the experiment. The participants were fairly divided into two groups (2D and 3D) based on age and background knowledge. This research work was approved by Ethics Coordination Committee of Universiti Teknologi PETRONAS, Malaysia.

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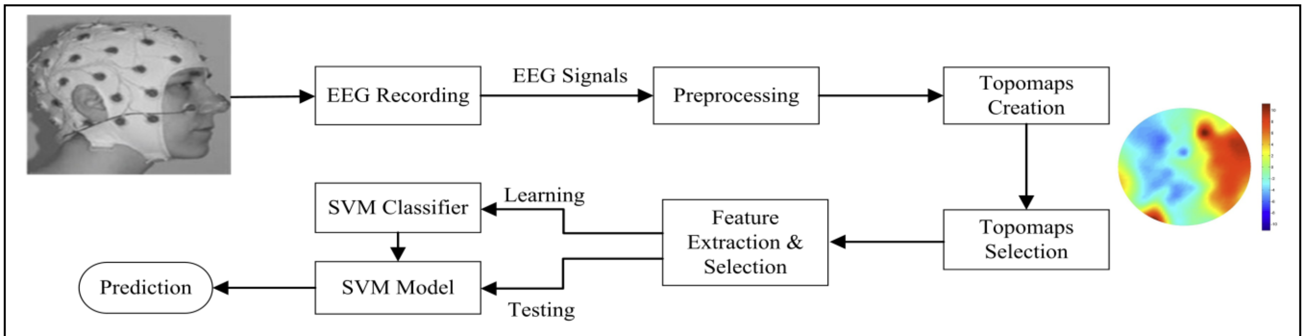

Figure 1. Diagram of the System

Learning Materials & Experimental Tasks: The 2D and 3D educational learning material used in this study was taken from Eureka 3D system (www.designmate.com). The contents were related to Biology course of level K-12 and none of the participant had background in this area.

The experiments consisted of two tasks: learning and memory recall. In learning task, each participant watched 2D or 3D learning material for 8~10 minutes depending on his/her group. Memory recall task was performed after thirty minutes of retention; in this task, twenty multiple choice questions (MCQs) about the learning materials were asked from each participant. Each MCQ had a question statement with four options for the answer. Participants were instructed to respond the answer by pressing a button from 1-to-4 depending on the choice which they think correct. The MCQs were same for both 3D and 2D groups. During the recall task, EEG cap was set and signals were recorded.

Both learning animations and MCQs of the recall task were presented on 41-inch TV screen, which was kept at a distance of 1.5 meter away from subject's eyes. The maximum time to answer one question was 30 seconds. If a question is responded correctly, it was assigned the label of '1' otherwise '0'. These correct and incorrect responses of each participant were used to separate correct (true memory) and incorrect (false memory) answers data.

EEG Recording: EEG recording corresponding to one question started when question appeared on the screen until the subject gave response to the question by selecting one of the four options for the answer; the maximum duration was 30 seconds. The start time at which question appeared on screen and the end time when the subject pressed answer button (response) were saved in an event file that was used to extract the part of EEG signal corresponding to the question. EEG data were recorded with a sampling rate of 250 samples per seconds using 128 channels Hydro Cel EGI Inc., USA. Some electrodes were noisy because of their locations on the scalp, so we selected 93 out of 128 channels by omitting the outmost electrodes.

Each recorded EEG signal is characterized by temporal and spatial distributions, and is represented by the spatio-temporal data matrix $X \in \mathbb{R}^{C\times T}$, where C is the number of channels and T is the number of sampled time points. We denote the scalp potential at channel c and time point t by $x_c(t)$, then EEG signal at time point t is represented by $X(t) = [x_{c1}(t), \ldots, x_{cC}(t)]^T$.

B. *Preprocessing*

A band-pass filter (1-48Hz) was applied on raw EEG data. Ocular artifacts were removed by using Gratton & Coles method [9] and all the EEG data were visually inspected.

C. *Creation of Topomaps*

The EEG signal $X(t)$ at time point t represents the voltages of the channels at the selected scalp locations, and it can be represented as a scalp map (topomap), which is an image. Therefore, we can use image processing and analysis techniques to extract features from topomaps. Using the recorded EEG signal and event information corresponding to each question, topomaps are created using EEGLAB toolbox [5]. Three sample topomaps are shown in Figure 2.

D. *Selection of Topomaps*

We noticed that many consecutive topomaps are similar and they do not contain any discriminative information. To get rid of this redundancy, we compare consecutive topomaps pairwise using some distance measure and select the most discriminative topomaps. Different distance measures are possible; for the sake of simplicity, we used cityblock distance. Pairwise distances of topomaps are calculated and the topomaps are ordered in descending order and M (= 20, 30, 50,100,120, and 150) topomaps with the highest dissimilarity selected, as shown in Figure 3.

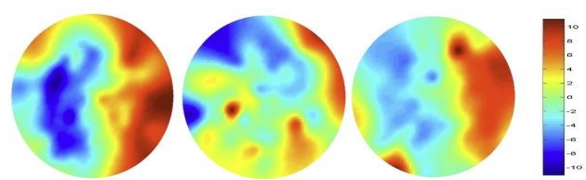

Figure 2. Three sample topomaps

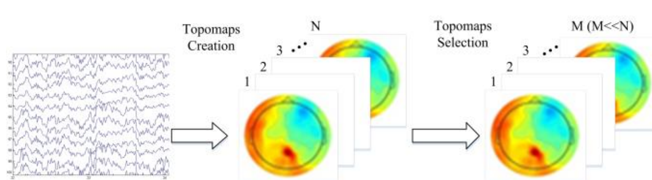

Figure 3. Selection of Topomaps

E. Feature Extraction

After selecting the most discriminative topomaps for each question, the next step is feature extraction. We extract texture information from each topomap using localized first order statistical features: mean (*m*), standard deviation (*std*), kurtosis (*kurt*), skewness (*sk*) and entropy (*ent*). We selected the statistical features which are commonly used to represent texture in various applications. We examined different combinations of the statistical features to find the most discriminative features for the problem under discussion. In our approach, for localized features, first we divide each topomap into $n \times n$ blocks; in our experiments, we tested two different numbers of blocks i.e. 16×16 and 8×8 blocks. Then we extract statistical features from each block and concatenate them into a vector. Figure 4 shows *i*th topomap and the corresponding feature vector V_i .

After extracting the feature vectors $V_1, V_2, \ldots, V_M$ from all the M topomaps selected for each question, we compute the vector $V = [v_1, v_2, \ldots, v_s]^T$, where v_i = mean ($v_{i1}, v_{i2}, \ldots, v_{iM}$), v_{ij} being the *i*th component of $V_j, j = 1, 2, \ldots, M$. The vector V represents the brain state corresponding to one question (sample). There are two reasons for computing V; first, if we concatenate $V_1, V_2, \ldots, V_M$, the dimension of the feature space becomes excessively large, and second, it captures the local discriminative information about brain states in a compact way. In case of concatenation, the dimension of the feature space is [#blocks × #features from each block × # topomaps] but in case of the proposed method, this dimension is [#blocks × # features from each block]), which is reduced by the order of the number of topomaps. For example, if 5 features are extracted from each block, and the number of blocks is $n \times n$, the dimension is reduced from $5n^2M$ to $5n^2$, where M is the number of topomaps.

F. Feature Selection

Since not all features are discriminative and also the high dimensionality of features causes computational problems and decline the prediction accuracy, so we need feature selection method to select the most discriminative features and discard the redundant ones. We used an efficient feature selection method that uses area under ROC curve to measure the importance of features and select the discriminative ones.

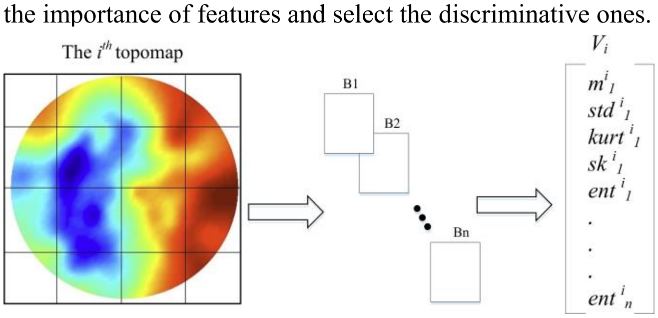

Figure 4. Feature extraction from one topomap, which is divided into 4x4 blocks.

G. Classification

True and false memory prediction problem involves two classes: correct and incorrect answers. For a two class problem, we can use any of the well-known classification techniques such as Neural Network, Support Vector Machines (SVM), Random Forests etc. As, in most of the applications, SVM gives excellent performance for two class problems because of better generalization ability, so we employed SVM. SVM is basically a linear classifier and kernel trick is used to handle the problems where data is not linearly separable. As Radial Basis Function (RBF) gives good performance in most of the cases, we employed SVM with RBF kernel; this involves two parameters. To find the best parameter values we used a grid-search method [6]. We implemented SVM using libsvm [7] library.

III. Results and Discussion

In this section, we present the results of the proposed system and discuss them. First, we describe the experimental setup that was used to perform the experiments. We selected a subset of the data to make sure that the samples used in modeling and testing the classifiers are true representatives of the two classes. The selected data was consisted of 200 questions: 100 with correct answers and 100 with incorrect ones. For the reason stated above, selection of the questions was not random, instead the correct questions were selected from the subjects who gave more correct answers and the incorrect questions were selected from the subjects who gave more incorrect answers. For performance evaluation of the system, 10 fold cross validation was used and the prediction rate was measured using the accuracy (the percentage of correctly classified correct and incorrect answers) and the area under ROC curve (AUC), which are two commonly used measures for evaluating a classification system. The accuracy and AUC were calculated as the mean accuracy and AUC for 10-folds.

A. Results

We modeled two classification systems, one for 2D educational contents and the other for 3D cases. We trained and tested each system using the data selected in the same way. Each system involves three parameters: number of selected topomaps, number of blocks and the number of statistical features computed from each block.

First, we selected 20 topomaps and divided each topomap into 8×8 blocks and extracted features with different combinations of first order statistics (1, 2, 3, 4 and 5) from each block, where 1 stands for mean only, 2 for mean and standard deviation, 3 for mean, standard deviation and kurtosis, 4 for mean, standard deviation, kurtosis and skewness, and 5 for all statistics. Other possible combinations can also be examined for better prediction accuracy. The best accuracy obtained by this method was 77.5% for 2D and 86.5% for 3D.

Keeping all other parameters fixed, we increased the number of blocks into 16x16. In this case, the accuracy increased and the best accuracy obtained was 82% for 2D and 89.5% for 3D.

Then we increased the number of selected topomaps per question to 30 topomaps and extracted features from 8x8 blocks. There was no significant improvement in accuracy for 2D, it reached 78% only whereas for 3D case, the improvement was significant and reached 92%, which is better than 86.5% obtained with 20 topomaps.

Also, we tried 16x16 blocks with 30 topomaps, and found that the accuracy was 81% for 2D, and 91.5% for 3D.

We increased the number of topomaps to 50 and tried 8x8 and 16x16 blocks. The accuracy for 3D did not exceed 92% that we got before, but it was increased and reached 88.5% for 2D case.

The results presented above indicate that the division of each topomap into 16x16 blocks gives better accuracy than 8x8 blocks. This is due to the reason that in the former case, the block size is smaller and local information is captured in a better way, which results in better discrimination.

To see further the impact of the number of selected topomaps, we selected 100 topomaps and repeated the same scenario to see the accuracy. This case gave us the best accuracy for both 2D and 3D, for 2D it was 96% and 96.5% for 3D. Using 120 topomaps, 2D reached 96% and 3D accuracy was improved and reached 97.5%.

Because we still got improved accuracy, we continued increasing the number of topomaps and selected 150 topomaps. In this case we got 96.5% accuracy for 2D and 97.5% for 3D using 16x16 blocks as shown in Table I (mean±std). Also, see the results for 8x8 blocks in Table 2.

TABLE 1. RESULTS WITH 16×16 BLOCKS AND 150TOPOMAPS.

#Features	**Accuracy**		**AUC**	
	2D	***3D***	***2D***	***3D***
1	95.5 ± 4.4	96 ± 3.9	0.97 ± 0.05	0.97 ± 0.04
2	96.5 ± 3.4	97.5 ± 3.5	0.95 ± 0.06	0.98 ± 0.03
3	86 ± 7.4	92.5 ± 5.9	0.87 ± 0.09	0.93 ± 0.08
4	85.5 ± 6.4	92.5 ± 7.6	0.86 ± 0.06	0.93 ± 0.08
5	86.5 ± 6.7	92 ± 6.3	0.88 ± 0.07	0.93 ± 0.07

TABLE 2. RESULTS WITH 8×8 BLOCKS AND 150TOPOMAPS.

#Features	**Accuracy**		**AUC**	
	2D	***3D***	***2D***	***3D***
1	91 ± 7	87.5 ± 6.8	0.93 ± 0.06	0.87 ± 0.10
2	95.5 ± 2.8	96.5 ± 3.4	0.95 ± 0.05	0.96 ± 0.07
3	93 ± 5.4	97.5 ± 3.6	0.92 ± 0.07	0.99 ± 0.01
4	93.5 ± 5.8	96.5 ± 4.7	0.92 ± 0.08	0.98 ± 0.04
5	93.5 ± 3.4	97 ± 2.6	0.94 ± 0.07	0.97 ± 0.04

By increasing the number of selected topomaps, the accuracy increased and reached the maximum accuracy using 150 topomaps. It is due to the reason that the more the number of topomaps, the more discriminative information is captured. Increasing the number more than 150 topomaps did not increase accuracy but the computational cost increased because it involved redundancy.

To know whether there is significance difference between 2D and 3D, we run each system 5 times by randomizing the datasets and 50 10-fold cross validation accuracies were obtained for each system using the system configuration which gave the best results. Using SPSS software, an independent t-test was applied depending on the assumption that normality is acceptable. There was no significant difference in the values for 2D (M=96.6, SD=3.7) and 3D (M=97.2, SD=3.3) groups; $t(98) = -0.847$, $p = 0.399$. These results suggest that there is no statistically significant difference between 2D and 3D in term of false and true memory discrimination in STM.

IV. CONCLUSION

We proposed a system for assessing true and false memories in case of STM by studying the effects of 2D and 3D educational contents and using EEG signals, which reflect the direct brain states. We associated true and false memories with correct and incorrect answers, instead of using only the subjective responses of participants (answers of the questions). This approach is more effective because it disregards the correct answer by mere guess and involves the actual brain states developed while giving correct or incorrect answers. Our analysis to the results showed that there is no significant difference between 2D and 3D educational contents in terms of true and false memory prediction in case of STM recall. The modeled classification systems can be employed to predict whether the answers of a subject are based on mere guess or learned information and it can be availed in truly assessing the memory recall ability of an individual participant, which can be helpful in selecting the right educational material and providing him/her guidance for his/her future carrier. The average accuracies of the systems are 97.5% in case of 3D and 96.5% in case of 2D, which indicate that there is still room for improvement. More discriminative features can further enhance the accuracy. Also, different classifiers can be tested to know which classifier can give the best result for this problem.

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