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Spatiotemporal Analysis of Visual Evoked Responses Using Dense EEG

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Abstract**—**A comprehensive study of object recognition in the human brain requires combining both spatial and temporal analysis of brain activity. Here, we are mainly interested in three issues: the time perception of visual objects, the ability of discrimination between two particular categories (objects vs. animals), and the possibility to identify a particular spatial representation of visual objects. Our experiment consisted of acquiring dense electroencephalographic (EEG) signals during a picture-naming task comprising a set of objects and animals' images. These EEG responses were recorded from nine participants. In order to determine the time perception of the presented visual stimulus, we analyzed the Event Related Potentials (ERPs) derived from the recorded EEG signals. The analysis of these signals showed that the brain perceives animals and objects with different time instants. Concerning the discrimination of the two categories, the support vector machine (SVM) was applied on the instantaneous EEG (excellent temporal resolution: on the order of millisecond) to categorize the visual stimuli into two different classes. The spatial differences between the evoked responses of the two categories were also investigated. The results showed a variation of the neural activity with the properties of the visual input. Results showed also the existence of a spatial pattern of electrodes over particular regions of the scalp in correspondence to their responses to the visual inputs.

Keywords**—**Brain activity, dense EEG, evoked responses, spatiotemporal analysis, SVM, perception.

I. Introduction

THE human brain is a very complex system [1]. The ability of the brain to categorize or group visual stimuli based on common features is a fundamental principle in cognition. This categorization is very fast and occurs in few millisecond time scales. In fact, the way how the brain regions activate/ communicate to produce cognitive functions is yet not well defined. EEG technique is well known to study waves representing the electrical activity of the brain. The main advantage of the EEG signals is its excellent temporal resolution (1ms), which is very crucial to track the brain activity in very short periods (about hundreds of ms), of most of cognitive activities [2]. EEG has an advantage in temporal resolution compared to fMRI. The continuous measure of brain activity via ERP derived from the EEG recordings is an important technique to investigate the time-course of activation of the different brain regions.

Given that, we need to track the brain activity during very short periods (about hundred of ms), the EEG has the capability to instantly read the states of the brain while avoiding the hemodynamic delay associated with fMRI. It is well known that in order to understand the visual processing, both spatial and temporal information of brain activities are necessary. A multivariate pattern classification has been used in [3] using together the MEG and fMRI and showed very high performance in understanding the object categorization in the human brain. This work has never been realized using dense EEG, which is the main objective of this paper.

Here, we used dense-EEG recorded during picture naming task combined with a Support Vector Machine (SVM) classifier to explore the possibility of discriminating between two categories of objects and animals from noninvasive EEG recordings. We finally explored the spatial locations of the most active EEG sensors over the scalp for each category of stimuli.

II. Materials and Methods

A. Participants

The participants were nine healthy volunteers: 5 women, aged 19-40 and 4 men aged 19-33 years. The subjects have reported having normal or corrected-to-normal vision and they did not suffer from any neurological disease. They have also given their informed consent to participate in this research study. The study and the consent procedure were approved by the National Ethics committee for the protection of persons (CPP), *conneXion* study, agreement number (2012-A01227-36), and promoter: Rennes University Hospital.

B. Experimental Protocol

A total of 148 displayed pictures on a screen using E-prime 2.0 software (Psychology Software Objects, Pittsburgh, PA) are used in our study. They were selected from a database of 400 standardized pictures and their order of display was randomized across the participants.

C. Procedure

The participants were tested individually in a soundproof dimly light room. Before the experiment the subjects were familiarized with the experimental pictures and their corresponding names. A trial consists on naming at normal

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speed a sequence of 148 randomly displayed pictures on a screen. Each picture appears during 3 seconds and is followed by a jitter-stimulus interval of 2 or 3 seconds randomly. In this task, participants were told to say the name of a picture aloud as rapidly and as accurately as possible. Most of the answers of the subjects were given while the image was still present at the screen. The spoken answers were digitized and recorded for later response latency and accuracy check.

D. EEG Acquisition and Preprocessing

EEG data were recorded with 256 channels covering the entire scalp. Fig. 2 (a) shows the distribution of all the electrodes. The main feature of this system is the large coverage of the subject's head by surface electrodes allowing for the improved analysis of the intra-cerebral activity from non-invasive scalp measurements, as compared with 32- to 128-electrodes standard systems.

Signals were sampled at 1 kHz with band-pass filters set between 3 and 45 Hz. Based on a visual inspection which followed each trial, epochs contaminated by movements, eye blinking or any other noise source were rejected and excluded from the analysis.

E. Classification

For classification purpose between the two classes Animals and Objects, we used a SVM algorithm. An SVM model is a representation of a set of different samples as points in a space divided into two categories with a clear and as wide as possible gap between them.

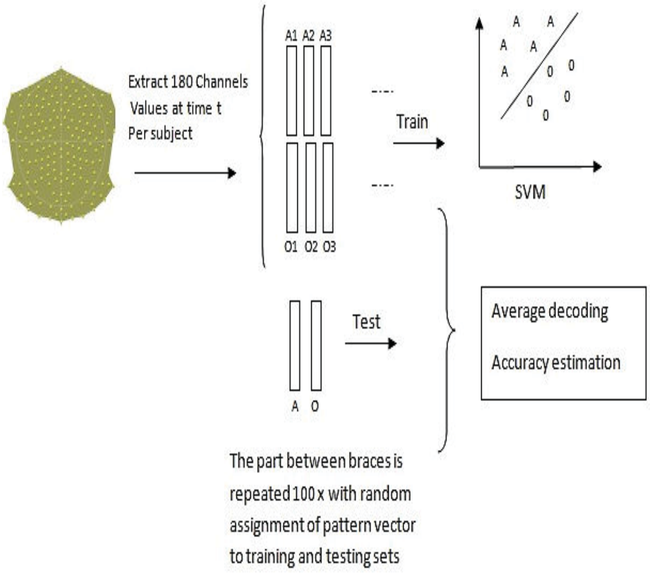


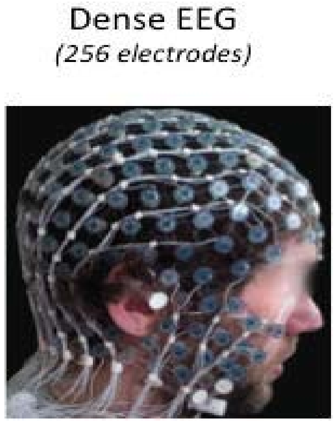
Fig. 1 Pipeline of the SVM analysis used to differentiate between the two categories Animals (A) and Objects (O) at each time point

In our application, we used an SVM classifier for each time point, to classify between two classes Animals and Tools. As illustrated in Fig. 1, we used supervised learning with a leave-one-out cross-validation approach, to train the SVM classifier to identify any of the two conditions [3]. We started by extracting randomly from dense EEG of different images including objects and animals, a set of training comprising all the observed vectors minus one which is left for the test phase. The process is repeated 100 times with random assignment of the data to training and testing sets, yielding an overall decoding accuracy of the classifier.

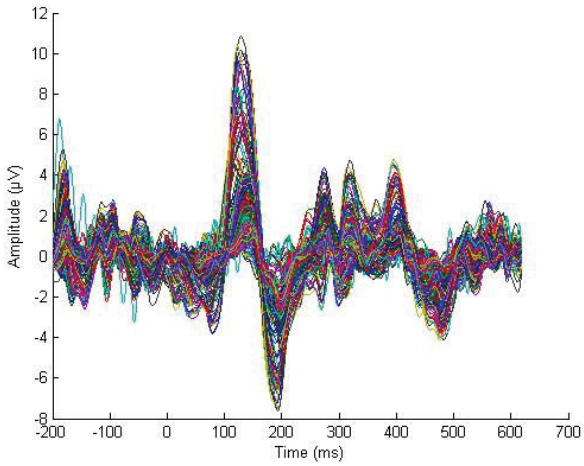
III. Results

A. Spatiotemporal Characteristics

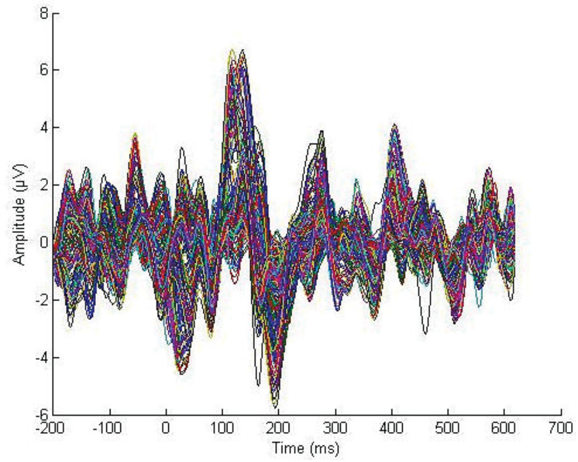
Fig. 2 (b) shows a typical example of ERP signals averaged over animals' stimuli for a particular subject while Fig. 2 (c) shows the signals averaged over tools stimuli for the same subject. As we see in the Fig. 2 the ERP signals have a close behavior on all the electrodes over the time acquisition. We can also point out that the maximum ERP value appears during the time interval (100-200 ms) for both cases.



(a)



(b)



(c)

Fig. 2 (a) Distribution of the 256 electrodes (EGI system), (b): ERP averaged over the electrodes for a particular subject for the visualization of the set of animals, (c): ERP averaged over the electrodes for a particular subject for the visualization of the set of tools

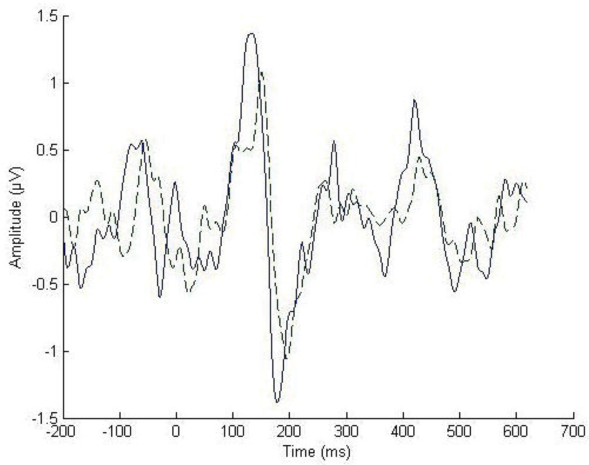


Fig. 3 Averaged ERP signals for Animals and tools

In Fig. 3, we show the global average (over all the subjects, trials and channels) of ERP signal for animals and objects. The figure shows the same global behavior for both conditions. However, we can notice a difference in the peak activation between both signals. The peak is computed as the maximal value which is attained by the ERP signal at the first 200ms after Onset. The peak corresponding to the signal for animal condition was about 149ms and the peak instant for objects is about 135ms.

B. Classification

In Fig. 4, we show the decoding accuracy greater than 65% at their corresponding time for two particular subjects. We can see that the maximal values for classification accuracy are in the interval (150-200) ms.

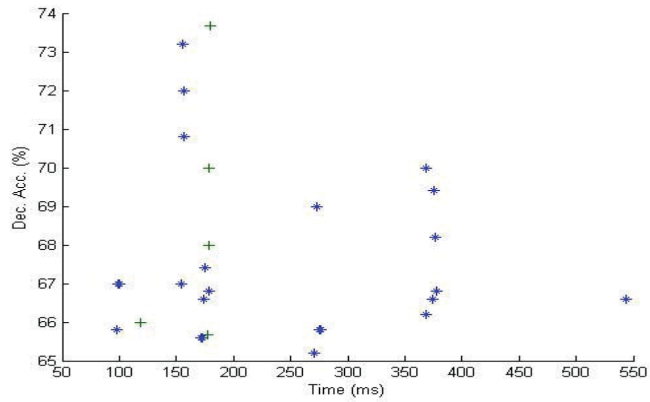


Fig. 4 Decoding Accuracy (>65%) per each time for two different subjects (*)

In Table I, we show the most energetic electrodes at the highest decoding accuracy for both of animals or objects.

TABLE I
LIST OF ELECTRODES WITH MAXIMAL CONTRIBUTION TO THE CLASSIFICATION TOOLS/ANIMALS

Subjects	Time of peak classification accuracy (ms)	Electrode where amplitude is maximal **Tools**	Electrode where amplitude is maximal **Animals**
1	155	AFP9h	FP2
2	420	F12h	TTP7h
3	490	P2Hp	Nz
4	180	T3	F8
5	253	FCC3	C4h
6	319	TTP7h	P6h
7	272	F12h	FP1
8	221	TP7h	PO6
9	572	P2hp	AFP10h

In table II, we show the distribution of the peak of classification accuracy for each subject as well as their occurrence time. In Fig 5, using EEGLAB [4] we show the corresponding energetic electrodes (square for animal experiment, circle for objects experiment) at the scalp. We mark the electrodes where the ERP amplitude is maximal at the time when the decoding accuracy is maximal. We can see in the Fig. 5 that frontal zone is globally the most contributing area to the classification task.

TABLE II
LIST OF MAXIMUM DECODING ACCURACY WITH THE CORRESPONDING OCCURRENCE TIME PER SUBJECT

Subjects	1	2	3	4	5	6	7	8	9
Max Dec. Acc. (%)	73	72	70	74	75	76	76	74	71
Time (ms)	170	300	270	200	250	300	250	220	151

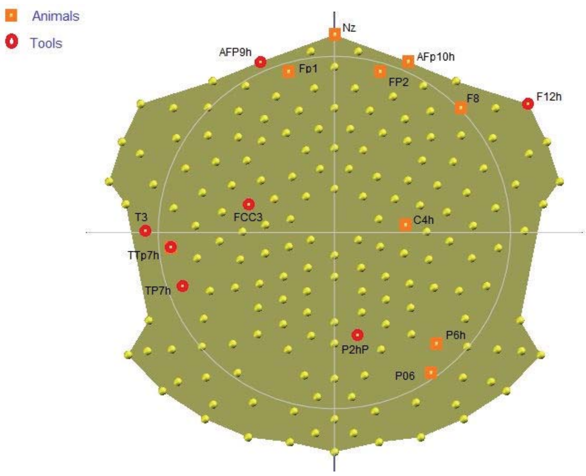


Fig. 5 Distribution over the brain of the electrodes contributing to the maximal values of decoding accuracies

IV. Discussion

In our paper, we used dense EEG during a picture-naming task of different categories of visual stimuli. The main advantage of this technique is its excellent time resolution (in the order of millisecond) and a very good spatial resolution (256 electrodes). The results obtained on nine subjects were very promising and showed a high performance of the dense EEG combined with the SVM classifier to differentiate between spatiotemporal patterns associated to different category of visual stimuli.

Despite the high inter-subjects' variability, the results showed that the time of discrimination between the particular categories lies mainly in the time periods related to the semantic processing. In addition, we think that other features could improve the presented study specially the approach's based on the analysis of the functional connectivity between brain regions at the scalp level (electrodes) [5], [6] but also at the level of the cortical sources using a recently proposed method called "dense-EEG source connectivity" [7].

V. Conclusion

In this paper, we reported a study to investigate the object recognition in the human brain using dense-EEG data. Results showed a difference in the discrimination of signals recorded during recognizing animals and objects stimuli. These preliminary results were very promising to understand the categorization of objects in the human brain from EEG that is a non-noninvasive and easy to use technology.

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