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Visual Decoding of Phrases from Occipital Neuromagnetic Signals

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Abstract— **Orthographic visual perception (reading) is encoded via a widespread dynamic interaction between different language centers of the brain and visual cortex. In this study, we investigated orthographic visual perception decoding with Magnetoencephalography (MEG), where phrases were visually presented to participants. We compared the decoding performance obtained with sensors within the occipital lobe that with whole-head sensors. Two naive machine learning classifiers namely support vector machines (SVM) and linear discriminant analysis (LDA) were used. Experimental results indicated that the decoding performance using only occipital sensors is similar to the performance obtained with all sensors within the task period, which were all above chance level. In addition, temporal analysis by taking short-time windows showed that the occipital sensors were more discriminative near onset compared to later time periods, while using the whole head sensor setup at later time periods performed slightly better than occipital sensors. This finding may indicate a sequential order (from vistual cortex to other areas beyond occipital lobe) during visual language perception.**

I. INTRODUCTION

Visual perception is a neural mechanism that allows the brain to create patterns of activity to receive, interpret, and act upon visual stimuli through a series of transformations of neural signals [1]. Orthographic visual perception is a "mid-level vision" process that acts as a central interface between visual and linguistic processing during reading [2]. The role of the occipital cortex, specifically ventral occipital-temporal cortex (vOT) is found to be crucial by several functional magnetic resonance imaging (fMRI) studies [3]–[6]. In regards to recognition of orthographic perception, several studies have attempted to explore pattern analysis using electroencephalography (EEG) [7], [8], fMRI [9], [10], electrocorticography (ECoG) [11], and magnetoencephalography (MEG) [12]. Very recently, beyond classification, research studies have attempted even for neural visual image reconstruction [13], [14]. These studies have focused on word-based stimu;i which constrains the complete understanding of visual lexico-semantic information that can be generated with a complete sentence/phrase. In addition, we hypothesize that the neural decoding paradigm on short-time windows might suggest a sequential order of visual language perception, where the neural activities start from visual cortex and then progress to other areas.

In this study, we used phrases as stimuli and explored the decoding of visual perception of language and the role of the occipital lobe as a measure of decoding performance. We used MEG to record the neural activity of healthy subjects while visually perceiving different phrases. MEG is a non-invasive neuroimaging modality which measures post-synaptic neuronal current-induced magnetic fields using highly sensitive magnetometers and gradiometers. It has a good spatial resolution (2–3 mm) and an excellent temporal resolution (< 1 ms) which make this modality ideal to study fast and dynamic processes such as language perception. The magnetic permeability of biological tissues (dura, scalp, skull) is similar to that of empty space and so the magnetic field recorded by MEG remain undistorted, which is a great advantage over EEG [15]. Moreover, MEG has been proven effective for numerous temporal dependence of visual pattern analysis research including optimal image discrimination [16], exploration on time-varying representation of visual patterns [17], decoding stimulus information while manipulating visual consciousness [18], time-series decoding of object recognition [19]. The high temporal resolution of MEG makes it advantageous over fMRI to explore on the temporal dynamics of visual perception.

The objective of this study was to compare the decoding performance of occipital sensors with the whole-head sensor setup to understand the role of the visual cortex in orthographic visual perception. Two machine learning classifiers, support vector machines (SVM) and linear discriminant analysis (LDA), were used to classify 5 different phrase stimuli from the MEG recordings. To further understand, the temporal dependency of perception mechanism, we compared the decoding accuracies from the occipital sensors with whole-head sensors by taking different short-time windows. Overall, the results show that the occipital sensors can decode the phrases well above chance level similar to while decoding with all sensors.

II. MEG METHODS

We used two identical Triux Neuromag MEG devices (MEGIN, LCC) (Figure 1) to collect neuromagnetic signals

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Fig. 1. The MEG unit with a subject and a stimulus “I need help” displayed on the screen

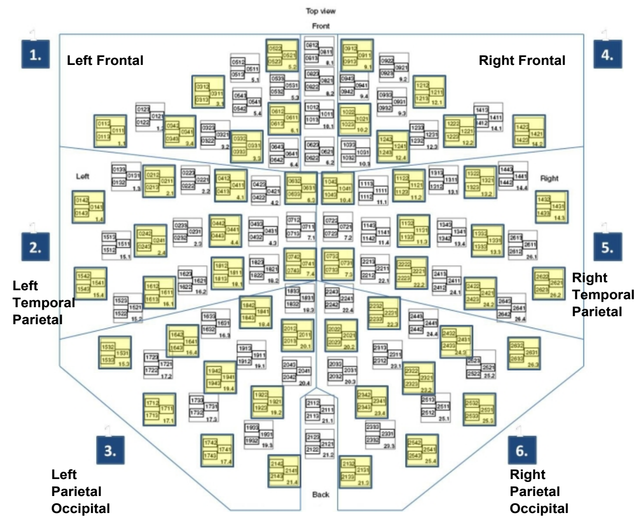


Fig. 2. The MEG sensor map: Modified with permission, from user manual ”TriuxTM” neo Instruction for Use, 2020 (MEGIN, LCC)

from 6 healthy subjects (2 females) with informed consent. We collected data at Dell Children’s Medical Center, Austin, TX, USA and Cook Children’s Medical Center, Fort Worth, TX, USA in compliance with the institutional review boards (IRB) of the participating institutions. The MEG system has 306 channels with 102 magnetometer sensors and 204 gradiometer sensors. The machine is housed inside a magnetically shielded room (MSR) to restrict external magnetic fields. we used 5 visual stimuli such as: *1. Do you understand me; 2. That’s perfect; 3. How are you; 4. Good-bye; 5. Ineed help*, those were displayed on a screen, one at a time, written in English. A stimulus dedicated computer running the STIM2 software (Compumedics, LTD) connected to a high-quality DLP projector was used to display the stimuli onto a back-projection screen situated at 90 cm from the subjects. Each stimulus was 1 s following a pre-stmuli interval of 0.5 s for 100 repetitions/trials in a pseudo-randomized order.

Data were recorded with a 4 kHz sampling rate with an online hardware filter of 0.03–1000 Hz. Bipolar electrooculography (EOG) and electrocardiograph (ECG) sensors were used for recording the eye movement and cardiac signals, respectively. The MEG signals were low-pass filtered below 250 Hz with a 4^{th} order Butterworth filter and resampled to 1 kHz. Line noise (60 Hz) and harmonics were removed with a notch filter. Only gradiometer sensor data were considered for decoding due to their effectiveness in noise suppression. Sensors that showed a flat or overly noisy response were discarded from analysis. Through visual inspection, trials containing large artifacts were removed with an average of 25% rejection rate. Data for one subject had only 63 valid trials for a phrase after preprocessing. Thus, for an unbiased comparison, we considered only the first 60 trials per phrase per subject for decoding. After preprocessing the signals were further processed through a db-4 wavelet denoising with 2 levels. Root mean square (RMS) values of the signals were computed as features for training the decoders. RMS features have been proven to be effective in language-based decoding studies [20]–[24].

III. Decoding Methods

A. Classifiers

We used two standard machine learning classifiers as decoders for the study. They are: support vector machines (SVM) and linear discriminant analysis (LDA). We used a second order polynomial kernel SVM following our previous studies [25]–[27]. The hyperparameters for SVM such as Kernel scale and C parameter were tuned and selected based on Bayesian optimization search. Automatic hyperparameter optimization was performed to find the best LDA parameters for Dirichlet distributions. The classification was performed for each subject with a 5-fold cross-validation (CV) strategy. For bootstrapping, the 5-fold CV was performed 10 times. The average accuracy across the 5 folds and 10 bootstrap runs was taken as the final performance.

B. Experiments

We performed two experiments to investigate and compare the visual decoding of phrases from occipital sensors and all (whole-head) sensors. First, we trained the decoders with the RMS features extracted from all sensors (~ 200) and then trained the decoders with RMS features extracted from occipital sensors only (~ 60) (Figure 2). Sections 3 and 6 of The MEG sensor map shown in Figure 2 which represent left and right parietal occipital cortex respectively were chosen as occipital cortex sensors altogether. Finally, we performed a temporal analysis where we extracted the RMS features from the perception segments with an increasing window of 100 ms starting from the stimulus onset and also with a decreasing time period of 100 ms from the onset. In other words, for increasing window analysis, the 10 time segments were [$1 - 100\ ms$; $1 - 200\ ms$; $1 - 300\ ms, ...1 - 1000\ ms$]. Similarly for decreasing window analysis, the time segments were [$1 - 1000\, ms$; $101 - 1000\, ms$; $...901 - 1000\, ms$]. We computed RMS features and performed decoding from each of these time segments.

IV. Results and Discussions

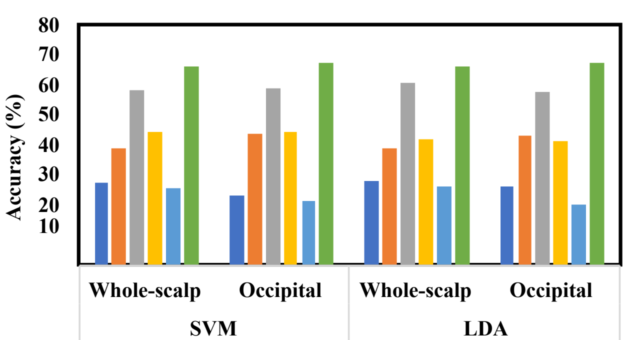
A. Occipital Lobe vs Whole Scalp

Figure 3 shows the comparison of decoding accuracies of visual phrases using all sensors and occipital sensors only for each subject using 2 classifiers. It shows that a similar accuracy was obtained with only occipital sensors (average=42.65%±3.01%) when compared to all sensors (average=43.5%±2.74%). This indicates that only occipital sensors might be sufficient for visual perception decoding. However, it might be also due to the possible inclusion of Wernicke's area sensors in the left parietal occipital cortex that is contributing to a similar accuracy. The performance of LDA and SVM was very similar as expected. Another important aspect to notice here is the consistency of performance for different subjects for these two groups (All and occipital). For example, the decoding accuracy was highest for Subject 6 while taking all sensors and also while taking occipital sensors irrespective of the decoders. Similarly, the performance of subject 5 was the lowest irrespective of the decoder and sensor group under consideration. Please note that the accuracies obtained for each subject and the average accuracy was higher than chance level (20% for a 5-class class classification).

These findings suggested that we may not need the whole-scalp sensors (~200) in MEG for visual perception decoding. Recently developed optically pumped magnetometer (OPM)-MEG [28]–[30] has shown potential for a wearable, low-cost, higher signal-to-noise ratio, and even shielding-free MEG. Our findings provide a support to reduce the number of sensors in OPM-MEG but can still obtain the similar performace in visual speech perception, which will significantly reduce the cost of the system.

B. Temporal Analysis

The results for temporal analysis averaged across subjects is shown in Figure 4 where it can be seen that for individual chunks of time occipital sensors perform slightly lower than



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when decoding was performed using all sensors. Interestingly, when the initial temporal information was removed the decoding accuracy was decreased with time for occipital sensors but remained more or less the same when all sensors were used as can be seen from decreasing window analysis. This suggests that the occipital sensors might be contributing to the pattern recognition during initial periods but for visual perception, sensors beyond occipital cortex might be contributing.

A 1-tail t-test was conducted between the performances of the short-time windows which resulted that the decoding performance of the whole-scalp setup is significantly higher than occipital lobe sensors only ($p < 0.05$) for both increasing and decreasing window analysis. These findings may suggest a sequential order of visual language perception, where the neural activities start from visual cortex and then to other areas. However, the difference in performance is just in order of 3-4%, thus, thus, further studies with larger number of participants are need to verify these findings.

V. Conclusions

In this study, we investigated the decoding of visual perception of phrases using MEG. We used two standard machine learning classifiers and compared the decoding performance of occipital sensors with all sensors and found that they perform similarly for decoding. MRMR based feature ranking method indicated that a higher number of sensors have better predictor score in whole-head sensors compared to occipital sensors only. Windowed temporal analysis indicated that the similar performance of occipital sensors and all sensors were mostly during the initial identification stage but the performance of occipital sensors decreased in the later time segments. Future study will focus on reconstruction of phrases from the neuromagnetic activity.

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Sub1 **Sub2** **Sub3** **Sub4** **Sub5** **Sub6**

Fig. 3. Comparison of decoding accuracies with All and occipital sensors for each subject

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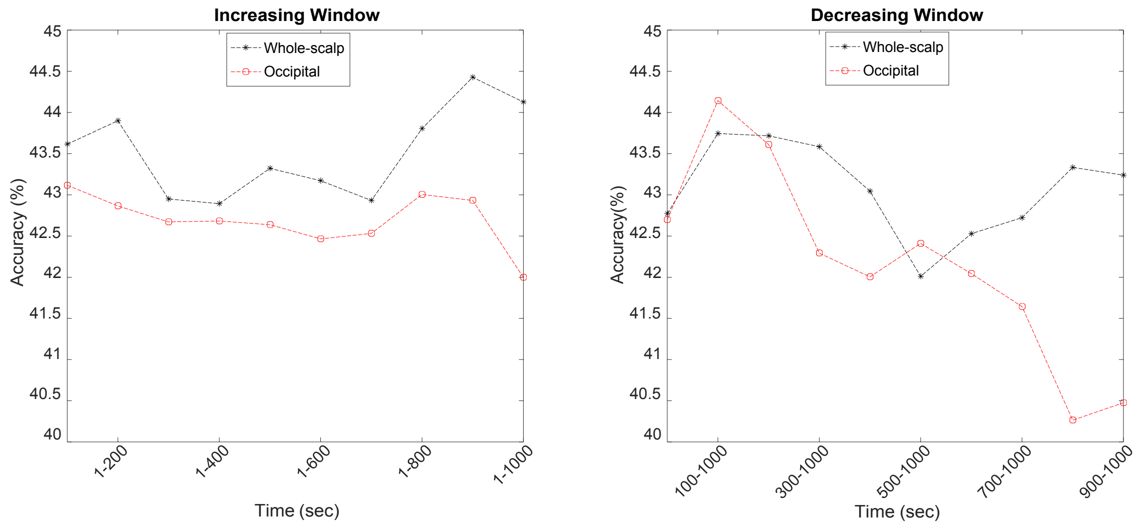

Fig. 4. Comparison of temporal analysis

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