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Otto-von-Guericke University  
Faculty of Electrical Engineering and Information Technology  
Chair for Healthcare Telematics and Medical Engineering



## Thesis

for obtaining the academic degree  
Master of Science (M.Sc.)

# Single Trial Decoding of Visual Spatial Attention Shifts from EEG and MEG Signals

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*Single Trial Decoding of Visual Spatial Attention Shifts  
from EEG and MEG Signals*

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# Abstract

**Purpose** Humans are constantly shifting their attention from one item to another. It has always been found that during a visual search task where attentional processing discriminates target and distractors, a particular event-related potential (**ERP**) component is elicited, known as **N2pc**. This thesis investigates whether visual-spatial attention shifts can only be extracted from a grand **ERP** average or decoded from a single trial.

**Method** To investigate the decodability at the single-trial level, binary classification of the **EEG** and **MEG** signals associated with the spatial attention shifts was employed by predicting the position of the attended target. The decoding accuracy is the number of correctly predicted target classes out of all the predictions. Implementing a spatiotemporal filter (**STF**) and generating combined trial datasets were included in the classification to increase the signal-to-noise ratio (**SNR**).

**Results** The obtained decoding accuracy reflected that the **EEG** and **MEG** associated with the **N2pc** were reliable to be decoded at the single-trial level. Mean decoding accuracy was reported to be higher with **STF** implementation and constantly increased as more combined-trial datasets were added. At the single-trial level, the mean decoding accuracy of **EEG** and **MEG** was 67.9% and 68.8%, respectively, and with **STF** implementation was 73.2% and 69.5%, respectively.

**Conclusion** Stronger discriminability to a relevant item among distractors in both visual fields could lead to more reliable **N2pc** in a single trial **EEG/MEG**, which drives better decoding performance.

**Keywords** Event-related Potentials, Attention shifts, **N2pc**, Selective Attention, Decoding, Classification, Support Vector Machine, Electroencephalography, Magnetoencephalography.

## Task of the Thesis in the Original:



FACULTY OF  
ELECTRICAL ENGINEERING AND  
INFORMATION TECHNOLOGY

### Task Description of a Master Thesis

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#### Topic

**Single Trial Decoding of Visual Spatial Attention Shifts from EEG and MEG Signals**

#### Task Description

In search displays humans can rapidly detect a target object located among distracting nontarget objects. Depending on the position in the visual field, the shift of attention to the target object is indexed by characteristic event related potentials (ERPs) as measured by electroencephalography (EEG) and obtained after averaging many repetitions of the stimulus. However, detecting these small interhemispheric differences on a single trial basis is challenging. Using EEG, it has been shown that averaging at least 3 repetitions of the stimulus is required to achieve an accuracy suitable to control a brain-computer interface. Magnetoencephalography (MEG) is the magnetic analogue to EEG, but provides complementary signals and a higher spatial resolution, which has been shown to reveal higher decoding accuracies in classification tasks.

The task of the student is to investigate the ability to decode from single trial EEG and MEG data in which visual hemifield a target object was shown. Two data sets will be provided for analysis. One of the datasets was already used for a different MEG study which has been published. The student will implement a decoding algorithm using adequate classification approaches. In the thesis the student will demonstrate how accuracy is changing when several trials are averaged and determine the accuracy as a function of trials involved. The results obtained by MEG data will be compared with the results obtained by simultaneously recorded EEG. Furthermore, the focus level was occasionally requested during the experiments. The student will investigate how the focus ratings correlate with the discriminability of trials.

Therefore, this thesis aims to find the answer of how does visual spatial attention shifts in EEG and MEG provide useful information for future brain-computer interface (BCI) studies. In a final analysis, the student will investigate the cause of failed behavioral responses, i.e. the unsuccessful processing of the stimuli, by predicting the attention shift according to the developed decoder.

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# **Declaration by the candidate**

I hereby declare that this thesis is my own work and effort and that it has not been submitted anywhere for any award. Where other sources of information have been used, they have been marked, directly or indirectly.

The work has not been presented in the same or a similar form to any other testing authority and has not been made public.

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Magdeburg, February 28<sup>th</sup>, 2022.

Esmondo, Ardiansyah Pringgo

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# List of Acronyms

**BCI** Brain-Computer Interface

**CCA** Canonical-Correlation Analysis

**EOG** Electrooculography

**EEG** Electroencephalography

**ERP** Event-Related Potential

**ERF** Event-Related Field

**hEOG** Horizontal Electrooculography

**LVF** Left Visual Field

**MEG** Magnetoencephalography

**MW** Mind-Wandering

**N2pc** N2-Posterior-Contralateral

**RVF** Right Visual Field

**SNR** Signal-to-Noise Ratio

**STF** Spatio-temporal Filter

**SD** Standard Deviation

**SVM** Support Vector Machine

**TPR** True Positive Rates

**vEOG** Vertical Electrooculography

# 1 Introduction

## 1.1 Motivation

In any crowded environment, the challenges in processing selective attention are eliminating non-necessities and coordinating our attention to the objective-related object. Humans can rapidly identify a target object scattered among distracting non-target objects in a visual search display where various objects compete for attention [1]. Depending on the position in the visual field, spatially shifting the attention to the target object is composed of characteristic event-related potentials ERPs as measured by electroencephalography (EEG) [2][3].

The human mind continuously shifts from wandering away out of the conscious perception of the external environment to focusing on their internal environment in their daily life. As a result, humans have to put more effort into countering this circumstance to maintain a good performance in an experimental task. A recent visual search experiment from Wienke *et al.* assessed neural response when participants covertly shifted their spatial attention to related target stimuli [4]. They found that the ERP component called N2pc as a neural marker of attentional selection [2][5][7] was higher in amplitude during mind-wandering (MW) phases [4]. Higher N2pc amplitude has been linked to greater attention on the relevant target item or distractor suppression in numerous previous studies (see for example [6][8]).

In typical ERPs experiments, the obtained neural signals from participants were averaged across many experimental trials containing stimuli to increase the signal-to-noise ratio (SNR). The ability to detect the small interhemispheric difference from a single trial is still unclear and challenging. One previous EEG study has shown that at least averaging three repetitions of trial has achieved accuracy suitable to control brain-computer interface BCI [9]. The ERP has the characteristic of having excellent temporal resolution but limited spatial resolution due to volume conduction by the skull [10–12]. Magnetoencephalography (MEG) as the magnetic analog of EEG [13, Ch. 2] provides more excellent spatiotemporal resolution [14].

Compared to numerous EEG-based BCI experiments, only a few BCI studies have incorporated the MEG, despite its advantage and feasibility in BCI [15]. Offline investigation revealed that the classifier based on support vector machine (SVM) performed well with MEC [16]. A study with simultaneous recording of EEG and MEG associated with finger movements revealed that decoding accuracy in classification tasks is greater in MEG than EEG [17]. However, the use of single-trial ERP decoding through classification is rarely developed, specifically on visual-spatial attention shifts.

Given the recent finding of visual-spatial attention shifts, this study will unravel the ability

to decode the **N2pc** as the marker of attentional shifts from single-trial **EEG** and **MEG** data in which the visual hemifield of a target object was shown.

## 1.2 Goals

This thesis aims to find the possible solution to the following research question:

“How many visual-spatial attention shifts can be correctly decoded from **EEG** and **MEG** data on a single trial level for future **BCI** applications?”

For this purpose, this thesis applies a decoding algorithm using an adequate classification approach. In the classification process, spatial filters are applied as a performance enhancer. In addition to single-trial accuracy, several trials are averaged to determine the accuracy of combined trial sets. Ultimately, the results from **MEG** data and the simultaneously recorded **EEG** are compared. The focus ratings are associated with trials discriminability to study the relationship between the behavioral responses from the experimental paradigm and the decoding outcomes. At last, investigate the cause of failed behavioral responses, i.e., unsuccessful processing of the stimuli.

## 1.3 Structure of Thesis

The chapters of this thesis are mentioned below.

- Chapter 2: Literature Review

This chapter will provide the appropriate theoretical context for the study by reviewing the literature from relevant fields.

- Chapter 3: Related Works

The related research, which offers a state-of-the-art approach, will be discussed in this chapter.

- Chapter 4: Method

In this chapter, the conventional and newly proposed methods will be discussed.

- Chapter 5: Results

Here all the final results of the proposed approach are presented.

- Chapter 6: Discussion

The final results and the implications will be discussed in detail.

- Chapter 7: Conclusion

As the final chapter, the findings of the thesis will be concluded.

# 5 Results

## 5.1 Decoding Performance of Single-Trial

The **EEG** and **MEG** decoding performances were obtained using our decoding approach, i.e., the 10-fold cross-validation of the linear **SVM**. From the results of the permutation test, the empirically estimated guessing level was averaged over subjects ( $i=13$ ), the usage of **STF** (with and without), and combined-trial sets ( $n = [1..10]$ ). It was 50.89% in **EEG** and 49.31% in **MEG** recordings, with their respective upper 95% confidence interval of 56.1% and 58.37%.

For the single-trial ( $n = 1$ ) **EEG**, the decoding accuracy of 12 out of 13 participants exceeds the chance level and outside the 95% CI of the permutation test ( $\mu = 67.927\%$ ,  $\sigma = 7.692\%$ ,  $max = 81.101\%$ , see Figure 5.1a), which was statistically significant ( $W = 91$ ,  $p < 0.001$ ) as reported by the Wilcoxon signed-rank test. In comparison, the decoding accuracy distributions in single-trial **MEG** are higher than the chance level and outside the 95% CI of the permutation test ( $\mu = 68.895\%$ ,  $\sigma = 8.4\%$ ,  $max = 81.154\%$ , see Figure 5.1b), which was also statistically significant ( $W = 91$ ,  $p < 0.001$ ). Thus, there was sufficient evidence to reject the null hypothesis ( $H_0$ ), indicating that visual-spatial attention shifts were reliable enough to be decoded at the single-trial level. Even though the decoding accuracy distributions within participants between **EEG** and **MEG** at the single-trial level appeared to be non-significant ( $W = 40$ ,  $p < 0.735$ ).

Aside from decoding accuracy, the **TPRs** of each class were displayed in Figures 5.1a and 5.1b, which defined the performance of the class-relevant trials. The **TPR** of class 0 (green dash) indicated how accurately visual-spatial attention shifts from **LVF** trials were decoded. The **TPR** of class 1 (pink dash) indicated how accurately visual-spatial attention shifts from **RVF** trials were decoded. In the single-trial **EEG**, the **TPRs** of both classes were not statistically significant ( $p = 0.08$ ; "0" :  $\mu = 68.846\%$ ,  $\sigma = 7.71\%$ ; "1" :  $\mu = 67.601\%$ ,  $\sigma = 8.131\%$ ). In the single-trial **MEG**, the **TPRs** of both classes were not statistically significant ( $p = 0.455$ ; "0" :  $\mu = 69.48\%$ ,  $\sigma = 9.395\%$ ; "1" :  $\mu = 68.352\%$ ,  $\sigma = 8.001\%$ ). **TPRs** of both classes remained not statistically significant even when **STF** was applied on both recording techniques and throughout different n-combined trials.

## 5.2 Decoding Performance in Different Conditions

The statistical analyses have the potential to reveal a recording technique (**EEG** and **MEG**)  $\times$  **STF** (with and without)  $\times$  the number of combined-trial sets ( $n = [1..10]$ ) interaction on decoding accuracy. The result showed no significant difference in recording techniques ( $F(1, 12) = 0.164$ ,  $p = 0.693$ ). Figure 5.2 depicts the mean decoding accuracy performance in which the **EEG** (blue bar) and **MEG** (orange bar) appeared about the same not only in the

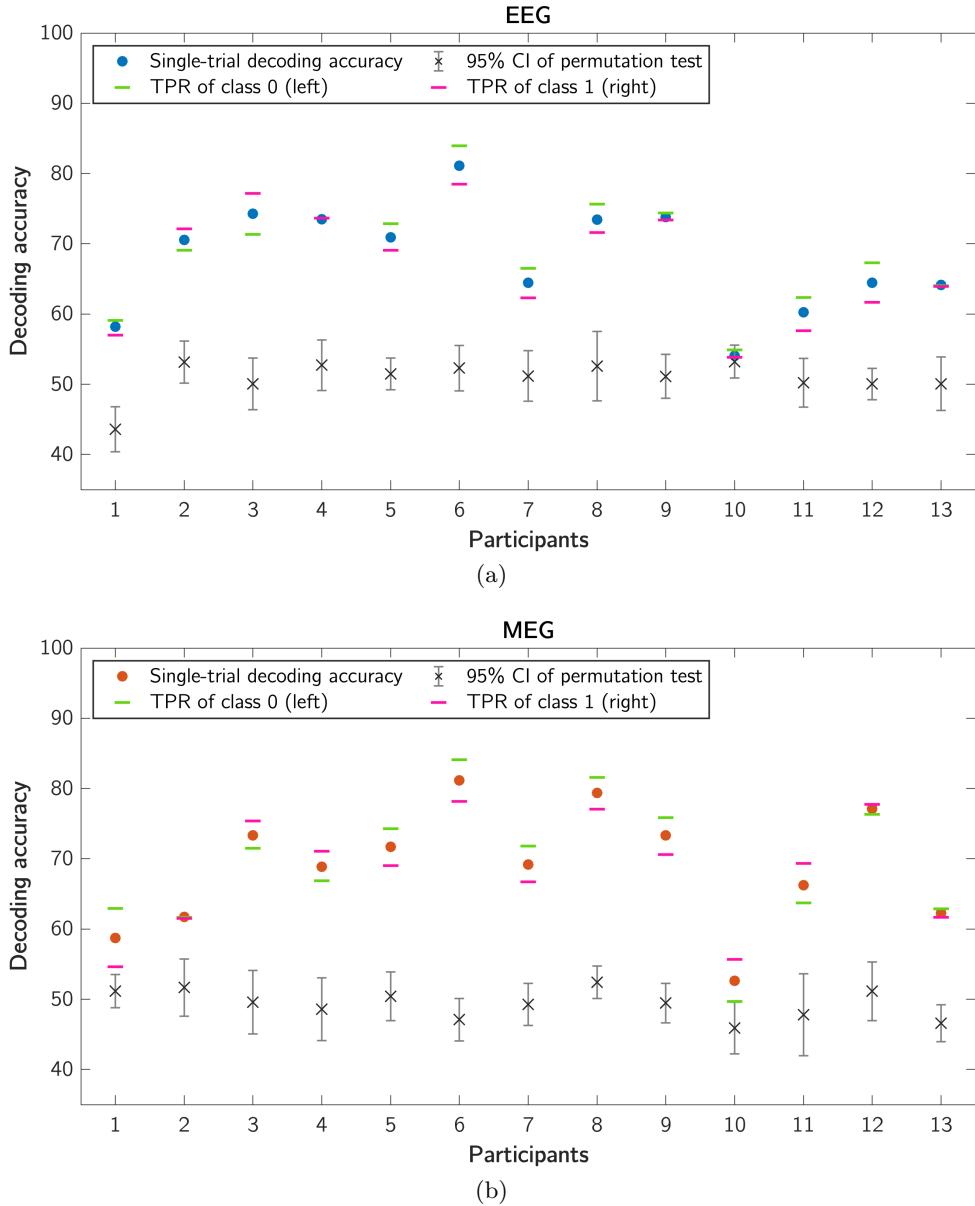


Figure 5.1: Decoding Performance of 13 Participants in Single-Trial Level.

a) The decoding accuracies in single-trial **EEG** (blue dot) were accompanied by the **TPRs** for class 0 (green dash) and class 1 (pink dash), which are primarily outside the 95% confidence interval for the permutation test (grey whisker with an x). b) The decoding accuracies in single-trial **MEG** (orange dot) with the same properties as already explained.

single-trial but also throughout combined-trial sets ( $n = 2 : 10$ ), with the mean decoding accuracy in **MEG** being slightly higher than in **EEG**. All values of mean decoding accuracy (corID) were summarized in Table 5.1.

On the other hand, the use of **STF** showed a significant effect on decoding accuracy ( $F(1, 12) = 58.731, p < 0.001$ ). The effect of **STF** was more dominant in **EEG** over **MEG** in each combined-trial set. In 5.2, **EEG** with **STF** (violet bar) always appears higher than **MEG** with **STF** (yellow bar). The significant effects on decoding performance were also shown as the number of trials to be averaged increased for combined-trial sets, i.e., from the single-trial  $n = 1$  to  $n = 10$

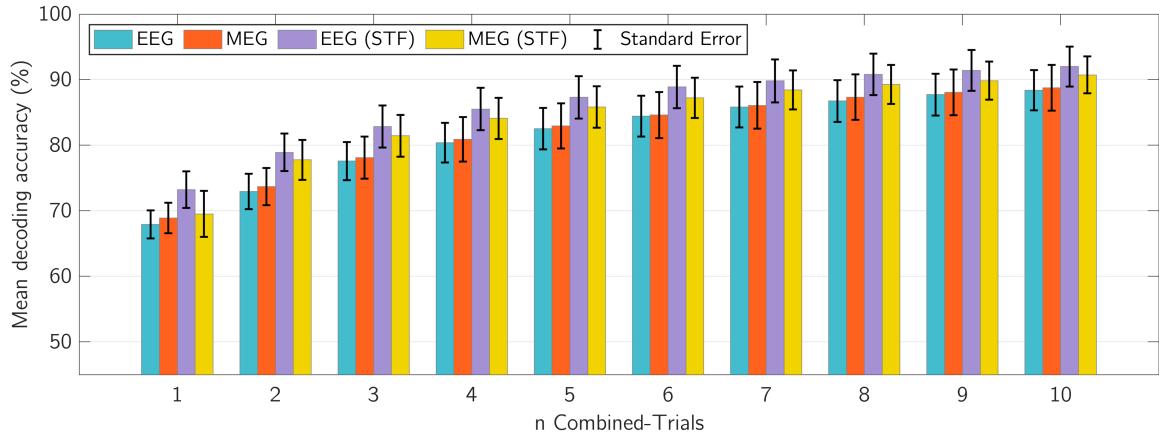


Figure 5.2: Mean Decoding Accuracy of EEG and MEG.

These are the primary findings from the current dataset regarding n-combined trials. Each bar is color-coded and described in the legend.

$(F(9, 108) = 235.012, p < 0.001)$ .

The increasing trend of mean decoding accuracy can be observed in Figure 5.3, along with the relative constant mean decoding accuracy of incorrect trials. An interaction of trial conditions (corID and badID)  $\times$  recording techniques  $\times$  STF  $\times$  n-combined trials was done. It revealed that no significant effect was observed in using EEG or MEG ( $F(1, 12) = 0.432, p = 0.523$ ). There were significant effects in applying the STF ( $F(1, 12) = 42.108, p < 0.001$ ), involving n combined-trial sets ( $F(9, 108) = 203.434, p < 0.001$ ), and the corID and badID were statistically significant ( $F(1, 12) = 295.176, p < 0.001$ ).

### 5.3 Decoding Performance Comparison with a Published Dataset

The datasets were compared based on the mean decoding accuracy across participants and each of the n combined trials. The distributions of the mean decoding accuracies were shown in Figure 5.4. The sign-rank test revealed that there was a difference in mean decoding accuracy between the present (orange bar) and published MEG (cyan bar) datasets ( $W = 49, p = 0.027$ ). However,

Table 5.1: Mean decoding accuracy of EEG and MEG

n	EEG	MEG	EEG (STF)	MEG (STF)
1	67.927	68.895	73.209	69.513
2	72.929	73.673	78.914	77.779
3	77.576	78.105	82.871	81.436
4	80.379	80.893	85.526	84.102
5	82.518	82.932	87.314	85.839
6	84.422	84.608	88.886	87.224
7	85.833	86.081	89.820	88.431
8	86.745	87.325	90.808	89.258
9	87.717	88.056	91.420	89.850
10	88.378	88.764	92.011	90.735

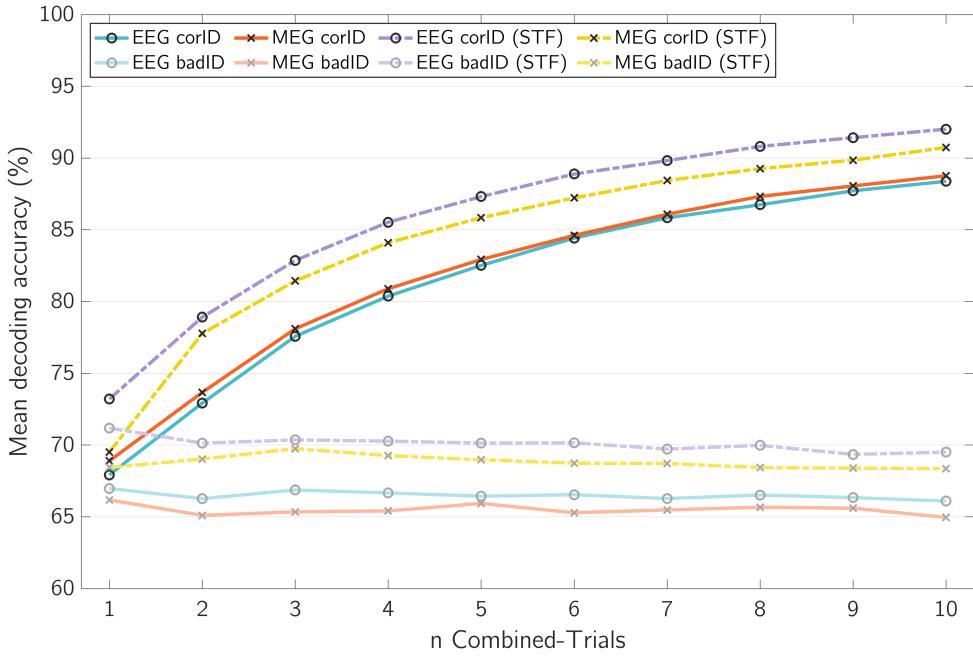


Figure 5.3: Mean Decoding Accuracy Trend of Correct and Incorrect Trials.

The mean decoding accuracies of EEGs and MEGs involving correct trials only (corID) significantly increased from single-trial to the highest n-combined trials, compared to incorrect trials (badID) with relatively over the same accuracy.

visual inspection of the mean decoding accuracy of each n did not show much difference between the present and published MEG datasets. After applying the STF, a significant difference was observed between the present (yellow bar) and published MEG (purple bar) datasets ( $W = 0$ ,  $p = 0.002$ ) with a better performance in the published MEG dataset.

#### 5.4 Focus Level and Decoding Accuracy Correlations

Correlation coefficients were calculated between the decoding accuracies and the focus level ON and OFF ratio when the participants responded correctly. The results showed no significant correlation and were visualized in scatterplot graphs with the linear relationship between two

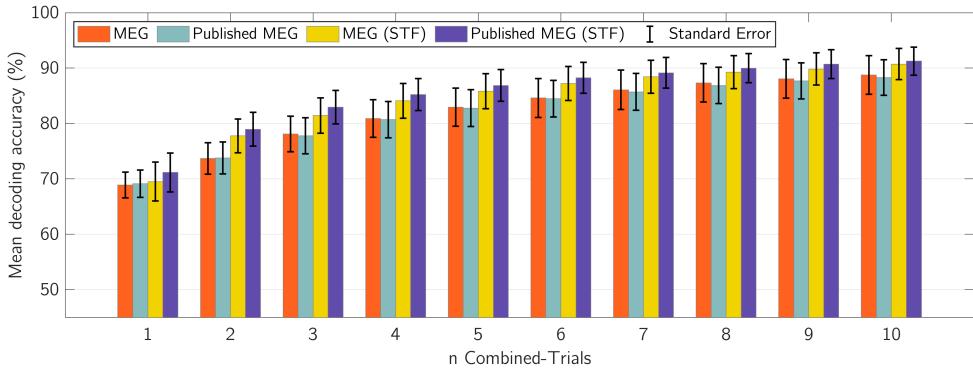


Figure 5.4: Mean Decoding Accuracy of MECI

A decoding accuracy results comparing the current MEG and published MEG dataset from Wienke et al. Each bar is color-coded and described in the legend.

Table 5.2: Mean decoding accuracy of current and published MEG datasets

n	MEG	$MEG_{published}$	MEG (STF)	$MEG_{published}$ (STF)
1	68.895	69.108	69.513	71.160
2	73.673	73.781	77.779	78.955
3	78.105	77.782	81.436	82.961
4	80.893	80.692	84.102	85.228
5	82.932	82.777	85.839	86.866
6	84.608	84.473	87.224	88.261
7	86.081	85.711	88.431	89.145
8	87.325	86.869	89.258	89.992
9	88.056	87.680	89.850	90.728
10	88.764	88.299	90.735	91.261

variables, Figures 5.5a for correlation between the single-trial decoding accuracy and ON trials ratio (EEG:  $r = 0.143$ ,  $p = 0.640$ ; MEG:  $r = 0.331$ ,  $p = 0.269$ ; EEG (STF):  $r = 0.261$ ,  $p = 0.39$ ; MEG (STF):  $r = 0.292$ ,  $p = 0.333$ ), and 5.5b for correlation between the single-trial decoding accuracy and OFF trials ratio (EEG:  $r = 0.395$ ,  $p = 0.181$ ; MEG:  $r = 0.311$ ,  $p = 0.301$ ; EEG (STF):  $r = 0.152$ ,  $p = 0.62$ ; MEG (STF):  $r = 0.408$ ,  $p = 0.167$ ).

## 5.5 N2pc Extraction Results

Target and distractors' disambiguation by participants evoked a visual attentional shift indexed by the N2pc component. The collapsed grand average ERP from contralateral (blue line) and ipsilateral (orange-dotted line) waveforms of all participants were illustrated in all parieto-occipital EEG channel pairs in Figure 5.6a. Contralateral minus ipsilateral (thick black line) displayed the N2pc with a more negative peak, which was also highlighted (grey shade) based on the significant difference ( $p < 0.05$ ) between contralateral and ipsilateral waveforms across participants. The N2pc can be seen to occur roughly in between 180ms to 300ms poststimulus on each electrode pair (see Table A.11). According to a visual inspection, N2pc showed prominent negative amplitude in P7-P8 and PO7-PO8 channels.

The grand average ERF of the left and right hemispheres comprised the chosen MEG channels in the occipito-temporal sites that showed maximum efflux and maximum influx collapsed into these grand averages, illustrated in Figure 5.6b. The LVF target waveform is represented with a blue line and the RVF target waveform with an orange-dotted line. The subtraction of RVF from the LVF target waveform revealed the mN2pc (thick black line) as a negative deflection ranging from 184ms to 354ms poststimulus in the left hemisphere and as a positive deflection ranging from 212ms to 330ms in the right hemisphere. The shaded grey area in both hemispheres reflected the temporal significances ( $p < 0.05$ ) when the mN2pc occurred.

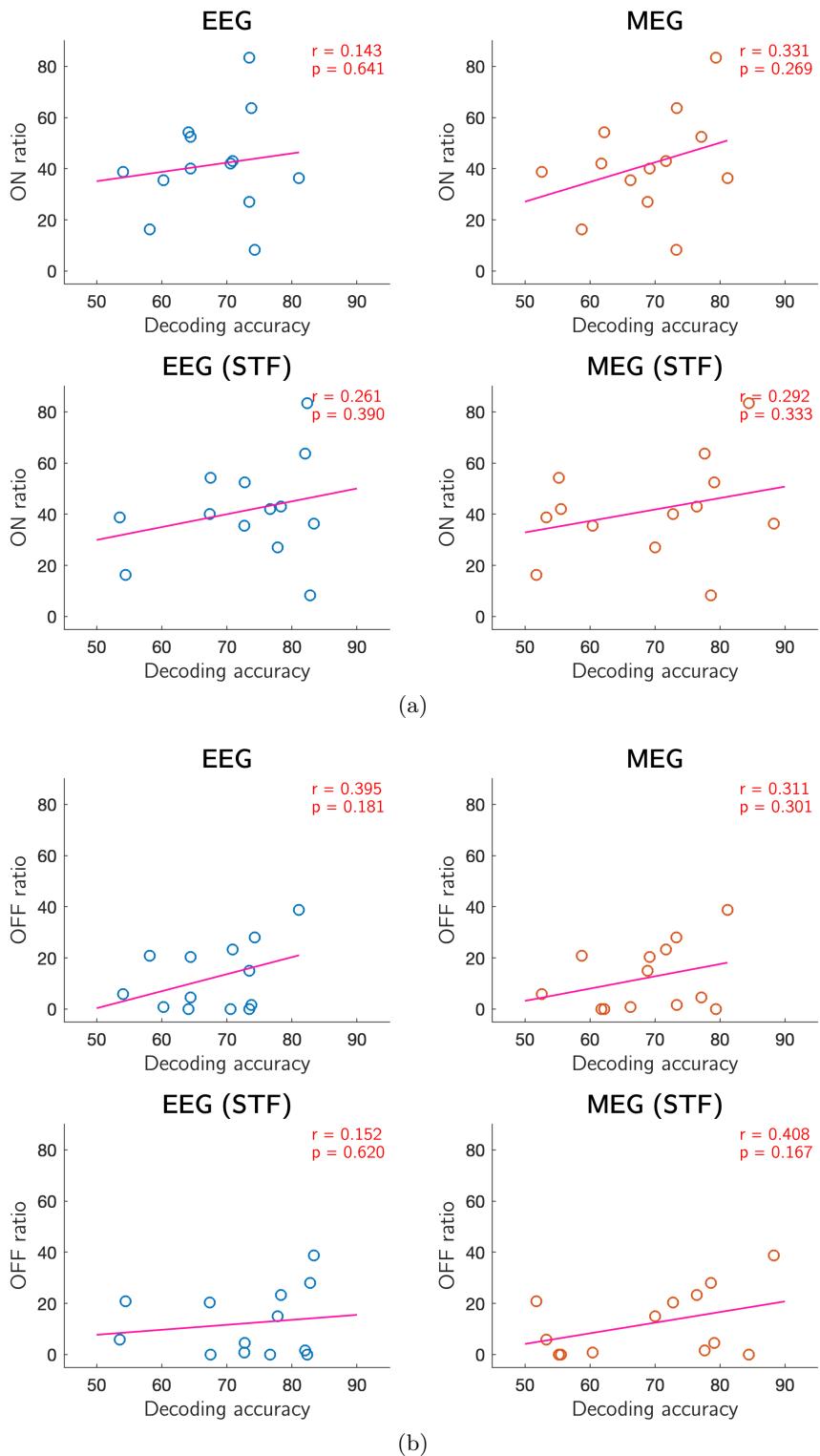


Figure 5.5: Correlation Between Decoding Accuracy and Mental State Ratings

- a) The correlation results from single-trial decoding accuracies against the ratio of ON trials and  
 b) the ratio of OFF trials

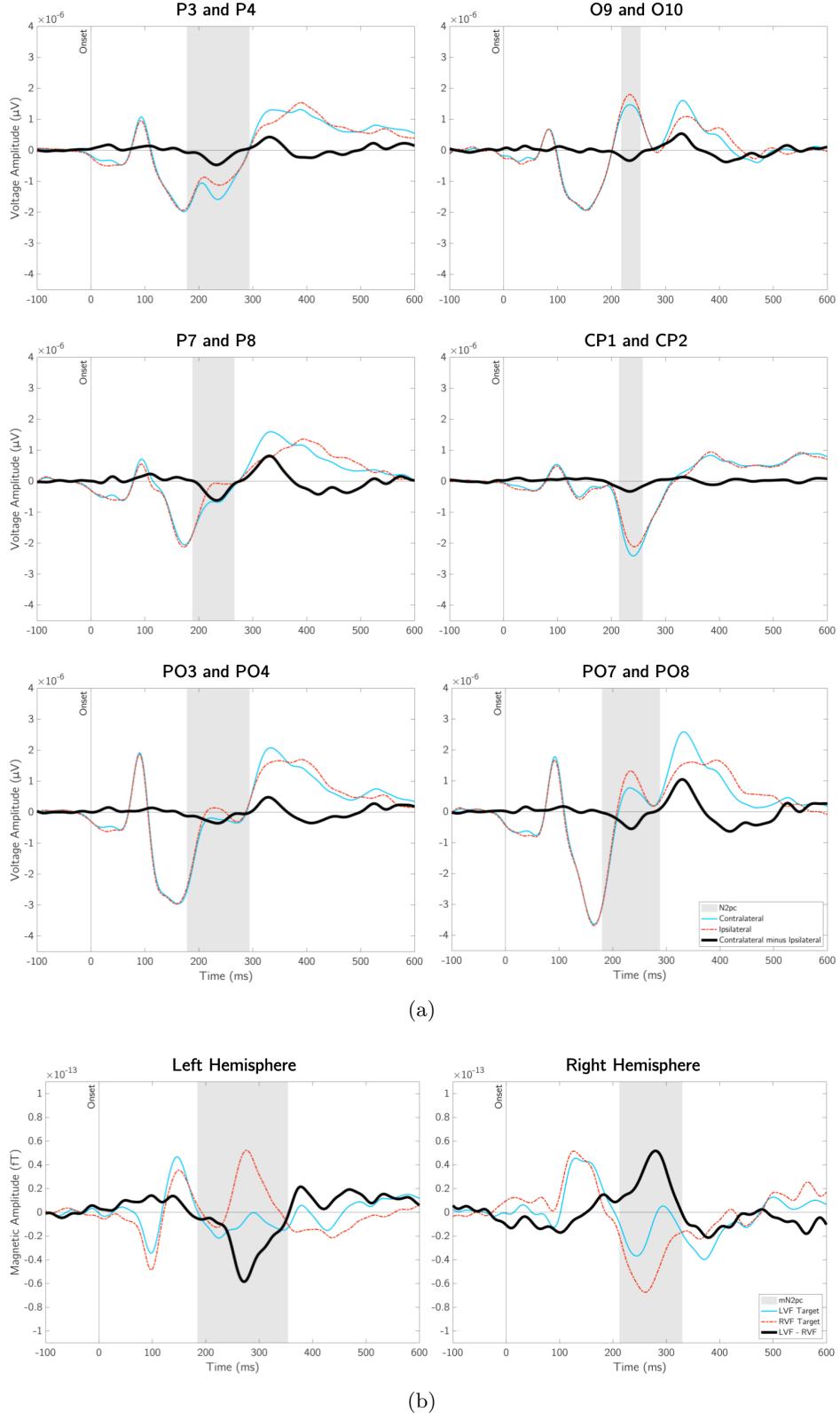


Figure 5.6: Grand Average of **ERP** and **ERF**.

a) Contralateral and ipsilateral waveforms for each **EEG** channel pair revealed **N2pc** activity in the grand average **ERP** at around 180ms to 300ms. b) The grand average **LVF** and **RVF** target waveform on the left and right hemispheres from the combination of efflux and influx channels showing opposite polarity **mN2pc** at around 180ms to 350ms.

# 6 Discussion

Numerous **EEG** and **MEG** studies have used the **N2pc** component in their visual attentional experiment. It offers a precise temporal neural marker that could track relevant target stimuli discriminated against other non-relevant distractors within the **LVF** or **RVF** in a visual task [3,7,31]. In the present study, the decodability of visual-spatial attention shifts or **N2pc** was being investigated from **EEG** and **MEG** signals by means of an **SVM** classifier.

## 6.1 Outcome

The utilization of **EEG** and **MEG** recordings in this study was not meant to be combined. Instead, the offline classification performances were observed between both. The first and principal observation was the **ERP** and **ERF** decoding performance at the single-trial level ( $n = 1$ ) involving the corID. It showed most individual decoding accuracies outperformed the permutation test and the chance level, which confirmed the hypothesis (see Section 4.5.1). From Table A.1, we can see the mean decoding accuracy was slightly higher in **MEG** than **EEG**, but they were not significantly different, and the decoding accuracy within participants did not indicate that **MEG** was overperforming **EEG**. Some of the individual decoding accuracy in **EEG** was higher than in the **MEG**.

After **STF** was applied, the mean performance was higher in **EEG**. This indicates that the application of **STF** enhanced the decoding accuracy across participants, with decoding accuracies in **EEG** being higher than in the **MEG**. Such performance was expected to be caused by **STF** since it has been known that a **CCA**-based spatial filter improves the SNR of the filtered signal [57]. The study of *Spüler et al.* performed **STF** based on **CCA** for their **ERP** classification. The **CCA** spatial filtering in **EEG** datasets provided consistent high accuracy results compared to other spatial filters [56]. The spatial filtering based on **CCA** was previously also used in [55,64,66,82]. They used **CCA** to approximate spatial filters and canonical components, which was adapted in this study for the single-trial and every  $n$ -combined trial set.

In the present study, adding the number of **ERP/ERF** trials to create the combined trial set was adapted from the study of *Awni et al.*. Their finding achieved almost 90% accuracy in one of the participants with only three trial combinations ( $n = 3$ ) [9]. While one of our participants reached a slightly higher decoding accuracy at 90.66% from **EEG** and 94.69% from **MEG**, with fewer **ERP/ERF** trials ( $n = 2$ ) and with **STF** applied. The combined trial set played a role in enhanced decoding accuracy. The more trial combined to create a new set, the more SNR increased. That is why the results showed improved performance as  $n$  was increased ( $n = [1..10]$ ). However, there was variability in decoding accuracy from **EEG** and **MEG** within participants,

which overperformed each other. According to *Awni et al.*, this variability is presumably due to the degree of familiarity of the N2pc response by the classifier [9]. Therefore, it is reasonable to conclude that visual-spatial attention shifts played a role in decoding performance.

While all the decoding performances results were generated from classification involving corID trials, another additional aspect was investigated to predict unseen badID trials using the trained SVM model. The badID essentially represented the behavioral response of the participants that were not successfully distinguishing the target in the visual paradigm. It was assumed that covert shifts might still occur even when the participants responded incorrectly. However, the results deduced that there might be a minor mistake in the decoding algorithm to process the badID trials. As demonstrated in previous results, the decoding accuracy should have increased as the number of combined trials increased. Instead, the decoding performance of badID was relatively the same over 70% accuracy as  $n$  increased.

The probability of the classifier that predicted each class correctly was considered the decoding accuracy of class-relevant trials (TPR of class 0 and class 1). The results showed that both TPRs were similar in all conditions (different recording techniques, STF involvement, different number of combined trials set), implying that the decoder is not biased to one of the classes. This was expected since the size of the class in each participant was balanced before the training with a randomized undersample.

The presented trials of ON and OFF mental state included only correct trials after erroneous trials exclusion, meaning that the ON and OFF ratio presented in the result was the proper outcome when participants confidently rated if they were focused entirely on the task or MW. However, the Pearson's correlation coefficient between the focus level ratio and obtained decoding accuracies showed a weak correlation and were not statistically significant in all conditions, implying that they are not correlated. It can be assumed that the subjective rating during the visual task did not affect the decoding performance.

In the study of *Wienke et al.*, only MEG was used to collect the data and has not been appropriately used for decoding analysis outside the study [4]. With the authors' permission, a decoding comparison was made between the published MEG dataset and the current MEG dataset. Since both MEG datasets were recorded with the same paradigm, the results showed expected performance with roughly the same mean decoding accuracy. Yet, the statistical result indicated that they were statistically significant ( $p = 0.027$ ). The mean decoding accuracy of both datasets was indeed improved across  $n$ -combined trials set but still with relatively the same value. In this case, no significant effect was seen on the data. However, the mean decoding accuracy improved after STF was applied on both datasets. It was also observed that the performance of published MEG was always higher than the current MEG across  $n$ -combined trials. In this case, it was reasonable to confirm the significant difference ( $p = 0.002$ ) in the mean performance between the current and published MEG. This is probably because *Wienke et al.* did not record EEG simultaneously. Hence the SNR was more excellent, and the combination of STF enhanced the performance even better.

At this point, the main goal of this thesis has been discussed. Additionally, the **N2pc** from **ERP** and **ERF** analysis was also investigated conventionally (see Method 4.3). In the grand average **EEG** waveforms, the **N2pc** was seen more prominent in parieto-occipital **EEG** channel pairs P7-P8 and PO7-PO8 at roughly around 180-300ms. This is aligned with the common theory that **N2pc** is commonly elicited near the PO7 and PO8 [31], which some studies sometimes also explored **N2pc** at P7 and P8 [91,92], or both [93]. In the grand average **MEG** waveforms, the mN2pc was seen as opposite-polarity in the left and right hemispheres, elicited at roughly around 180-350ms. Unlike **EEG**, the grand average of **MEG** was composed of influx-efflux maxima channel at the occipito-temporal site from each participant [7,62,75].

## 6.2 Limitation and Future Work

This thesis is a preliminary approach to creating a decoding algorithm of attentional shifts component for future **BCI** paradigm. Therefore, it is crucial to point out the shortcomings of the current approach to avoid them in the future.

The decoding approach was mainly employing the linear **SVM** classification. However, the classifier was not optimized using different optimization or combining different classifiers to improve the performance as suggested by *Lotte et al.* [52]. Therefore, future **BCI** development may consider another more adaptive and advanced classifier, e.g., [48].

Although the decoding accuracy was higher than *Awni et al.*'s findings, the classification process was not repeated 500 times as they demonstrated. Instead, the classification was repeated only ten times inside the cross-validation due to limited computer memory and time constraint. However, this is algorithm-dependent, meaning if a better decoding algorithm was found to produce robust performance, certainly we don't need 500 times repetitions.

The decoding accuracy was not computed during ON and OFF trials because each participant did not have an insufficient and imbalanced number of trials to perform the classification. Some participants did not even have any trial left, presumably due to **MW**, which led to the erroneous response, and they were excluded accordingly.

# 7 Conclusion

The work of this thesis was developed to address the following research question:

“How many visual-spatial attention shifts can be correctly decoded from **EEG** and **MEG** data on a single trial level for future **BCI** applications?”

Answering this question, this thesis demonstrated a decoding algorithm using **SVM** classification in 10-fold cross-validation to decode the visual-spatial attention shifts, i.e., **N2pc** from **EEG** and **MEG**. The classifier model determined which side in the visual field the target was attended to, which cannot be performed using the conventional **N2pc** method. During the classification, the dataset was performed with and without **STF**. These processes were initially investigated at a single-trial level then increased the number of trials to create n-combined trial sets ( $n=[1..10]$ ) for each classification and participant.

The main results revealed that the **N2pc** was reliable to be decoded at the single-trial level with adequate performance. A participant achieved 81.101% decoding accuracy in **EEG** and 81.154% in **MEG**. The decoding accuracy was enhanced when **STF** was applied, and every time the n-combined trials were increased. Ultimately, the results from **MEG** data and the simultaneously recorded **EEG** were compared, it was revealed that both decoding accuracy was not statistically significant. The focus ratings ON and OFF ratio were compared with the decodability, and they appeared not correlated. An investigation to compare the published **MEG** dataset by *Wienke et al.* with the current **MEG** dataset showed the published dataset was high in performance than the current dataset after the involvement of **STF**.

The work of this thesis had revealed the reliability of the decoding algorithm based on **SVM** classification managed to decode the visual spatial attention shifts indexed by **N2pc** from **EEG** and **MEG** signals in a single trial. Better decoding accuracy was influenced by **STF** implementation and increasing n-combined trials. However, **STF** enhanced the decoding accuracy better in **EEG** than **MEG**. It can also be concluded that more trials to create a combined or noise-reduced dataset were better since SNR was also increased and led to higher classification accuracy. These finding has led us to conclude that the decoding accuracy is driven by the level of **N2pc** effects reflected by spatial attention. The characteristics of the **N2pc** component in **EEG/MEG** can be adapted as **BCI** control, considering the obtained robust performance. However, the challenge is to overcome a reasonable classification time consumption, as better accuracy involves many repetitions. The stronger presence of discriminability of the relevant item from the distractors in **LVF** and **RVF** would generate reliable **N2pc** in a single trial **ERP/ERF**, which drives better decoding performance. Therefore it was possible to assume that if the decoding performance were not optimal, it could be caused by the failure of processing the stimuli by participants, meaning that the spatial attention shifts were not present. It could also be caused by **MW**.

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