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Tracking Attention Through Time

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Abstract

Temporal attention refers to directing attention to a certain location at a specific point in time. It has been suggested that attention can be measured through steady state visual evoked potentials (SSVEP), which refers to an increase in frequency power in the brain that coincides with the frequency of a flickering stimulus. Previous studies have found that the SSVEP can reflect attention modulation, meaning the difference between attended and non-attended stimuli. It has also been found that SSVEP can be used to investigate temporal attention. We aim to investigate the temporal dynamics of temporal attention. We used SSVEP in an attentional task and a timing task to track how the SSVEP changes across the duration of a trial. We applied and compared three different methods of SSVEP analysis, namely a Region of Interest (ROI) selection, a selection of electrodes with the highest signal-to-noise ratio (BE), and rhythmic entrainment source separation (RESS). We did not find any significant attention modulation in any of the methods. We did find that RESS weights were more distributed in non-occipital areas, which was not reflected in the electrode selection of the best electrode method. We also found that RESS resulted in higher SSVEP power and SNR overall. We suggest that these results may indicate that SSVEP signals from temporal attention drift through attentional networks throughout the scalp, rather solely being reflected in occipital regions. We also suggest that temporal attention might manifest as a transient response, rather than a sustained power increase. Our findings call into question the notion that temporal attention is characterized by a sustained increase in power. They also emphasize the influence specific types of SSVEP analysis methods may have on the findings of a study.

Tracking Attention Through Time

Successfully shifting attention between stimuli is a key part of how we perceive the world. Visual attention involves focusing on what we look at, and also where and when attention is directed (Mora-Cortes et al., 2017; Babiloni et al., 2004, Lockhofen & Mulert, 2021). Visual attention can be assessed through a variety of psychophysical methods, such as electroencephalography (EEG). In this study, we aim to investigate the temporal dynamics of visual attention and how it behaves in the time-frequency domain, as well as assessing three methods for maximizing signal-to-noise ratio for EEG signals.

Tsotsos and colleagues (1995) described visual attention with their "Selective Tuning Model". Vision uses a hierarchy of processing of visual events in the visual fields. Due to the hierarchy of the visual system, visual input from distinct sources in the visual field may activate overlapping neurons at the highest level in the hierarchy. This is also referred to as "cross-talk". According to Tsotsos and colleagues (1995), attention may resolve the issue of cross-talk through Selective Tuning. This model sees visual attention as a process that operates upon the hierarchy, starting at the top, selecting units with the highest response. Then the process moves down the hierarchy, pruning all inputs that do not contribute to the selected units. The end result is a spotlight highlighting selected units, with irrelevant information being suppressed. Thus, when multiple stimuli are available, visual attention is selecting a relevant stimulus, and actively suppress irrelevant stimuli (Tsotsos et al., 1995; Vissers et al., 2017; Toffanin et al., 2009).

Temporal attention of visual attention refers to the ability to predict the onset of an event, and direct attention at the right time (Babiloni et al., 2004; Mora-Cortes et al., 2017). Rohenkohl and colleagues (2012) assessed the effect of temporal expectation on visual sensory information in an orientation discrimination task, and found that predictable target intervals increased signal strength and reduced reaction times compared to unpredictable targets. Similar effects have also been found in other psychophysical experiments, where investigating the N2pc event-related potential (ERP) suggested that temporal attention accelerated stimulus processing, as the N2pc onset was earlier when participants utilized timing information in a visual search task (Rolke et al., 2016). The effects of temporal expectations have also been associated with higher prestimulus alpha power, which has been found to be important for temporal attention (Gruber et al., 2014), when visual targets were presented in a predictable time interval (Min et al., 2008).

One way of assessing attention through EEG is with frequency tagging. Frequency tagging allows tracking of the focus of visual attention by measuring the Steady State Visual Evoked Potential (SSVEP) elicited by a stimulus. SSVEP is a rhythmic neural response to a flickering stimulus, where the neural frequencies match the frequency of the attended stimulus (Mora-Cortes et al., 2017; Ales et al., 2012). Specifically, when looking at a stimulus that flickers at a certain frequency, the amplitude of the corresponding frequency and its second harmonics should increase (Mora-Cortes et al., 2017). By measuring the amplitude of neural frequencies corresponding to the flickering stimulus, one may infer whether or not the stimulus is being attended (Toffanin et al., 2009). Over the course of 3 experiments, it was demonstrated that SSVEP-amplitude did not significantly differ between covert or overt attention, suggesting that SSVEP may be an attentional response rather than a purely visual response (Phyo Wai et al., 2020). Temporal dynamics of attention could also be investigated through SSVEP by looking at the dynamics of amplitude modulations. Modulation of frequency power over time has previously been used to assess the dynamics of attention (Vieweg & Müller, 2020). This increase in power modulation was also found to be directly related to behavioral performance of visual short-tern memory, which is thought to be a mechanism strongly linked to visual attention (Bundesen et al., 2011; Vissers et al., 2017). Taken together, it can be assumed that higher SSVEP-related frequency amplitudes may reflect more attention, and that the increase in frequency power over time may be used to track attention through a time-course.

Traditionally, analysis of SSVEP data involves examining activity from a single electrode or a cluster of electrodes that show the clearest response to rhythmic stimulation, also referred to as “best electrode approach” (BE) (Cohen & Gulbinaite, 2017). However, this method has multiple limitations which introduces subjectivity in the electrode selection, such as how one justifies the electrode selection, or which electrodes are the best to select. BE also involves limitations which negatively affect the signal-to-noise ratio (SNR), such as difficulties in isolating SSVEP from ongoing brain activity in the same frequency range (Cohen & Gulbinaite, 2017). Due the limitations of the BE approach, Cohen and Gulbinaite (2017) developed an SSVEP analysis approach named rhythmic entrainment source separation (RESS). RESS has previously been used to assess SSVEPs in the blind hemifield of patients with hemianopia (Sanchez-Lopez et al., 2019), where the method was used to successfully increase the SNR. However, RESS can suffer from overfitting, where the filter picks up noise in the absence of a signal (Vissers et al., 2017, Cohen & Gulbinaite, 2017). This can be dealt with by defining the spatial filter based on data with the same flicker frequency across all conditions.

RESS has been used repeatedly since its development (Sanchez-Lopez et al., 2019; Mora-Cortes et al., 2017; Vissers et al., 2017; Zuure et al., 2020; Gulbinaite 2017), but no studies have yet attempted to investigate the difference between RESS to other methods of electrode selection. The general idea of RESS is to create a spatial filter weighting different electrodes by the extent to which power at different frequencies at these electrodes increases the SNR. We aim to compare RESS to BE and a predefined cluster of electrodes which we call a region of interest (ROI) method. In order to assess whether RESS improves the identification of the time course of attention-related power modulation.

This study aims to assess the temporal dynamics of visual attention, and to explore the dynamics of SSVEP determined with different methods over time throughout a trial. Although it has already been established that SSVEP can be used to assess visual attention, it has not yet been used to investigate the temporal dynamics of temporal attention. Therefore, we set out to explore whether we can use the temporal dynamics of SSVEP power changes to track attention over time in a temporal attention task. In other words, we aim to investigate how the SSVEP related power modulations behaves in relation to temporal expectations. We also sought to investigate the difference between RESS, BE and ROI. RESS is meant to increase SNR (Cohen & Gulbinaite, 2017), but it still cannot be assumed that this improvement will translate when assessing data over time.

We administered a covert temporal attention task while using EEG, where the participants had to switch attention between targets on predictable time-intervals. The data will then be analyzed using RESS, BE, and the ROI approach. We expect the SSVEP power to steadily increase towards the onset of the target stimulus, indicating an attention modulation over time. Given the previous success of RESS to filter EEG signals, we also expect that this method should result in a higher signal-to-noise ratio, and thereby larger power modulations. We also administered a temporal reproduction task, or timing task, in order to assess the timing ability of the participants. An exploratory comparison will be made between the SSVEP observed during the attention task and the temporal reproduction task, in order to investigate the effect attention may have on the observed SSVEP.

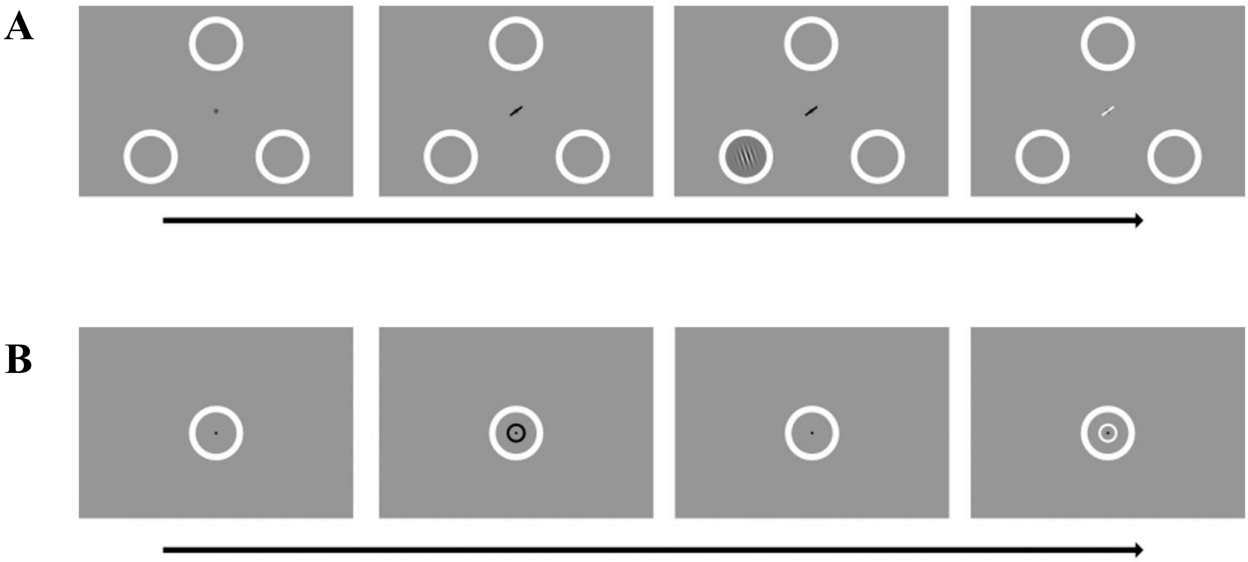
Methods

Participants. Data was collected from 30 healthy participants with normal or corrected-to-normal vision. Participants were required to have no history of photosensitive health conditions or seizures. Participants were first- or second year psychology students (12 male, 18 female), and were compensated with partial course credits upon completion of the study. 2

participants were excluded due to technical difficulties. Prior to the experiment, all participants signed a consent form after being given thorough information about all procedures.

Procedure and stimulus presentation. The experiment was conducted in a darkened, sound-attenuated room. The participants were seated between 50cm and 60cm away from a 24-inch LG-22MB37 LED monitor with a refresh rate of 100Hz, controlled by an HP Compaq Elite 3800 PC with a 3.3Ghz Intel i3-3220 processor with 1024 X 768 resolution. The experiment was developed and presented using OpenSesame (Mathôt et al., 2012) with the psychopy backend (Pierce, 2007).

Figure 1



Note: General trial sequence for (A) Attention task and (B) Timing task.

For the attention task, each block started with three flickering circles (13Hz, 15.5Hz and 18Hz) appearing on the screen, together with a fixation dot and a pointer pointing to the location of the next target. The stimuli were circles at 300px eccentricity, positioned at the top center (13Hz), bottom-right (15.5Hz) and bottom-left (18Hz). The radius of each circle was 100px, drawn with a width of 45px. The fixation dot had a radius of 8px. The length of the pointer was 60px. The target was a tilted Gabor patch that would appear inside one of the three stimuli for 100ms. The circles stayed on the screen until the end of the block. The attention task consisted of three different time intervals (800ms, 1400ms and 2000ms) between pointer and target onset (See Figure 1A for trial sequence). The participants were asked to indicate whether the target stimulus, was tilted to the left or right. Once the Gabor patch had been presented, the pointer turned white, signaling that a response can be given. The response was given by pressing the “Z” key if the stimulus was tilted to the left, and the “M” key if the stimulus was tilted to the right. The location of the next target was indicated using a black pointer that would point towards the location of the upcoming target. The next target position would always in the next location in a clockwise direction, making everything fully predictable. The angle of rotation of the target was continuously modulated using a staircasing procedure, making the difficulty of the task dependent on participants' performance. In the staircase, being correct twice in a row would decrease the angle by one step, while being incorrect once would increase the angle by one step (Meese, 1995). This staircase would not be reset between blocks, but continued throughout all blocks.

The attention blocks were interspersed with a temporal reproduction task (Figure 1B), where the target and fixation dot were located in the center of the screen. The temporal reproduction blocks all started with a flickering circle that remained on screen throughout the block. The circle would flicker in either 13Hz, 15.5Hz, or 18Hz in different blocks. Each new trial started with the presentation of an open black circle inside the flickering circle for either 800ms, 1400ms, or 2000ms. After 500ms, a white circle would appear inside the flickering circle. The participants would have to reproduce the duration of the black circle with the white circle by pressing the space bar to make the white circle disappear at the right moment. The black and white circles had a radius of 30px, and were drawn with a width of 13.5px. The fixation dot had a radius of 8px.

The experiment consisted of 48 blocks of ten trials each, as well as three practice blocks. This included twelve blocks for each time interval in the attention task, and twelve blocks for the timing task. Before a block started, participants would be informed of the upcoming block type and of the interval duration in case of an attention block. After each attention block, participants would get feedback on their accuracy in the block they had just finished, and the current rotation of the target. And after each timing block, participants would be informed of their average deviation from the target in milliseconds Participants could take a break between blocks, and they were given a longer break approximately halfway through the experiment.

EEG acquisition and data cleaning. EEG data were recorded via a Waveguard 64-channel EEG cap, and recording was controlled by eego™mylab software by AntNeuro. The 64 electrodes were placed according to the standard 10-20 system. The cap consisted of 62 + 2 + 1 = 65 electrodes. There were 62 scalp channels, 2 mastoid channels, and 1 EOG electrode located underneath the left eye.

We analyzed and processed the data offline using MNE-python (Gramfort et al., 2013; Gramfort et al., 2014). First, we used a high-pass filter at 0.1Hz to remove slow drifts. Next, various methods described below were applied to mark and remove non-usable data. For these methods we rely on data from so-called preprocessing epochs. These epochs comprised data from 800ms before to 200ms after either target onset or offset of the white and black circle, to ensure a maximum amount of task-related data and a minimum amount of non-task related data. Note that these epochs were not used for the SSVEP analysis described later.

Detection of noisy channels was performed by following the PREP-pipeline (Bigdely-Shamlo et al., 2015) and utilizing the RANSAC algorithm from the autoreject package (Jas et al., 2017). RANSAC creates permutations of the dataset where channels are removed at random, trying to predict channel data of the removed channels through interpolation of the activity from the remaining channels. If more than 40% of the permuted data shows a low correlation between predicted data and observed data (r<0.75), the channel is considered faulty. These channels were primarily peripheral channels, and did not overlap with occipital electrodes where we expected the SSVEP to primarily manifest. These channels would be discarded from subsequent preprocessing, and their data was interpolated from the remaining channels at the end of preprocessing.

Data of interest may be contaminated by noise from muscular activity (Muthukumaraswamy, 2013). Therefore, we attempted to identify muscle artefacts and remove epochs that contain contaminated data. To do this, we administered a procedure adapted from the PREP-pipeline (Bigdely-Shamlo et al., 2015), which is also provided by FieldTrip (Oostenveld et al., 2011). The assumption for this procedure is that muscular activity produces high-frequency power across multiple electrodes simultaneously. Contaminated data were identified by utilizing a 110-140Hz band-pass filtered version of the dataset. We computed its Hilbert envelope, and filtered the results with a 200ms boxcar averaging window. This results in a per channel estimate of high frequency power activity. Based on data in the preprocessing epochs, we compute a per-channel median and median absolute deviation. These were used to compute a Z-score per channel for all data. When the Z-score, averaged across all channels, exceeded 5.0, the data were flagged as contaminated data.

Eye blinks were identified and removed through the use of ICA (Independent Component Analysis). For this, we sub-sampled a new high-pass filtered dataset at 100Hz and filtered at 1.5Hz in order to identify rapid increases in frequency power. Subsequently, independent components were computed using Picard ICA (Ablin et al., 2018). Resulting components were then visually inspected to identify those corresponding to blinks. In order to validate the selected components, ‘Blink epochs’ were defined as 1000ms windows around local maxima in the 1-10Hz band-pass filtered VEOG signal: The selected ICA components were the only components with a high correlation to the VEOG signal in these epochs ($R^2 >$ .5).

To ensure that our EEG-measures reflect covert attention, we needed to identify and discard trials with eye movements. An ERPLAP-inspired procedure (Lopez-Calderon & Luck, 2014) was used to identify eye movements, meaning we filtered EOG channel data by convolving it with a stepwise kernel, which formed a zero-mean filter of 325ms that went from -1 to 1 via a 25ms linear ramp. Potential eye movements were defined as local maxima and minima in this signal exceeding the 90^{th} percentile. However, we found that both blinks and eye movements were being characterized by sudden changes in the EOG signal, and detected by this method. Therefore, short EOG epochs around potential eye movements were created (+/-200ms). Within this time window we could dissociate between the two, as eye-movements were characterized by step-like jumps in amplitude, while blinks were identified by a U-shape. Using these characteristics, we determined the amplitude difference at the beginning and end of this epoch, divided by the peak-to-peak amplitude deflection within the epoch. Using a cutoff of 0.7, a small number was taken to be a blink, and a large number was likely to be an eye-movement.

The preprocessed data were used to construct epochs of the trials, using cleaned data of the 2 seconds after pointer onset in order to see the entire time course of all attention trials. Any epochs overlapping with contaminated data were discarded.

SSVEP and data analysis. We applied ROI, BE and RESS to the raw dataset. This was followed by creating epochs of the trials, resulting in an amplitude time course for each method.

For the region of interest method, we subset the seven electrodes of interest (Pz, PO3. PO4, POz, O1, Oz and O2) and applied narrow bandpass filter for each frequency of interest

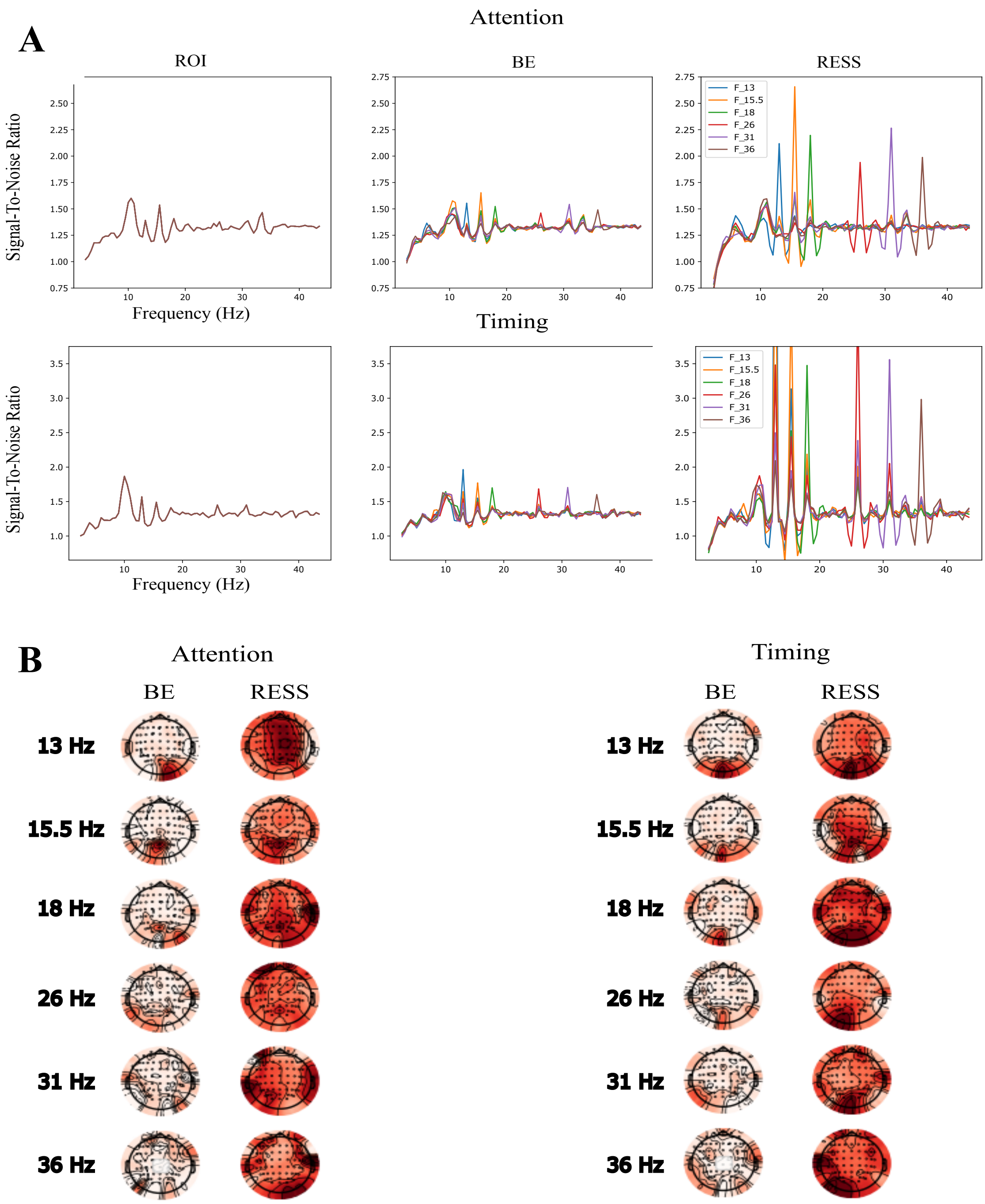
+/- 0.5Hz. We then computed the Hilbert Envelope, and average that across the seven channels.

BE had a similar procedure, but instead of seven predetermined electrodes, the chosen electrodes were the 5 electrodes with the highest SNR for each frequency of interest (13Hz, 15.5Hz and 18Hz) during the task, based on the FFT power spectrum. This power spectrum was computed from 2s epochs for each trial. For the attention task, these epochs range from .5ms to 1500ms after the pointer onset. For the timing task it was 1000ms before to 1000ms after the onset of the white circle. To determine the SNR, we computed the average power at the frequency of interest, divided by the average power at reference frequencies. The reference frequencies were two neighboring frequencies on either side at a resolution of .5Hz, after skipping the direct neighbor (i.e., for 13Hz, the reference would be power at 14Hz and 14.5Hz on one side, and 12Hz and 11.5Hz on the other side).

In order to compute RESS, three versions of the signal filtered at the frequency of interest, and for each neighboring frequency for reference are created. These versions are also based on the FFT power spectrum (See Above). Based on these three frequencies, three covariance matrices are constructed. A PCA like algorithm is then performed to extract eigenvectors that maximally dissociate the frequency of interest covariance matrix from the reference covariance matrix. These eigenvectors are used to obtain RESS component time series which can be analyzed instead of the data from individual channels. For a more thorough description, we refer to Cohen and Gulbinaite (2017).

Results

Figure 2



Note: SNR spectrograms for the three methods and topomaps of frequencies of interest and their second harmonics. RESS topomaps reflect the average normalized weight assigned to each electrode, where the absolute value of the weights are divided by their maximum value per participant. Best Electrode topomaps visualize the amount of times an electrode was selected in BE across all participants. (A) SNR spectrograms for each method. Each row depicts a different task. (B) Topomaps from the attention and timing task.

The spectrograms (Figure 2A) show average SNR across all participants, while the topomaps (Figure 2B) shows the distribution of the electrode selection and RESS weights over the scalp. A 2-way Repeated Measures ANOVA was performed on the SNR data of both the attention and timing task to analyze SNR as a function of Frequency of Interest (FOI), method and their interaction. There was a significant effect for FOI, $F(2, 71) = 8.899$, $p < .001$. This indicates that the SNR differs between the frequencies. For example, the SNR in the frequencies of interest is typically higher than at the second harmonics. There was also a significant effect of method, $F(1,29) = 301.559$, $p < .001$. This means that at least one of the three methods had a significantly different SNR than the others. There was a significant interaction ($F(3,76) = 5.887$, $p < .001$), suggesting that the effects of each method on SNR differed across frequencies of interest. Further exploration showed that a 1-way ANOVA at each target frequency yielded a significant effect of method with all $p < .001$ after Bonferroni correction for multiple comparisons. Pairwise comparisons showed that SNR is significantly higher with RESS than with both BE and ROI, and that the SNR with BE is significantly higher than with ROI, with all $p < .034$ after Bonferroni correction. The timing task yielded similar results in both the RM-ANOVA and the pairwise comparison. However, for the timing task, the overall SNR was found to be higher than the SNR in the attention task. Taken together, these results suggest that RESS yields the highest SNR, and that the effect that the method has on SNR varies between frequencies.

To investigate how the different methods lead to such different SNRs, we created topomaps of electrode selection in BE, and of the scalp distribution of the RESS weights (Figure 2B), which allowed us to qualitatively compare the two. We expected that overall, both methods would show a lateralization in the contribution of different electrodes, which should coincide with the locations of each flickering circle (15.5Hz on the left hemisphere, 18Hz on the right hemisphere and a central focus for the 13Hz).

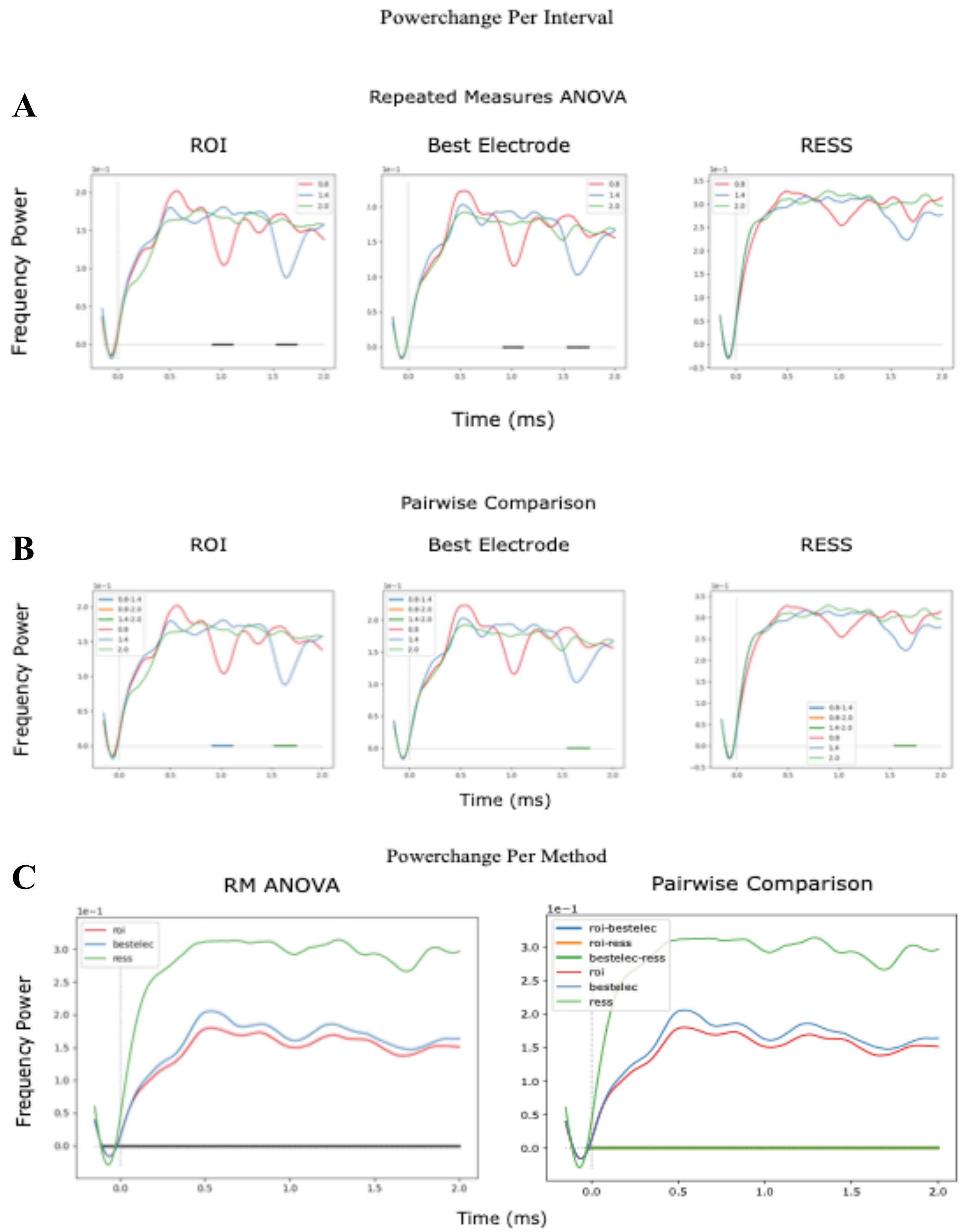
The topomaps for BE depict the amount of times each electrode was selected. The plots illustrate that mainly occipital electrodes were selected. This is not surprising, as the SSVEP is a visual response by definition. For 13Hz, BE seems to select occipital electrodes located at the medial and right hemisphere. The tendency to select right hemisphere electrodes is surprising, as the 13Hz circle was located at the center of the screen. For 15.5Hz, the method selected mostly occipital electrodes. Although a leftward bias can be identified, there is also a selection of electrodes in the right hemisphere. Lastly, for 18Hz, the most frequently selected electrodes are occipital electrodes. A rightward bias is present, although not very prominent as many of the selected electrodes are medial, and the clearest right hemisphere cluster reflects extrapolated data outside of the area of the electrodes.

The RESS topomaps show the scalp distribution of the absolute values of the RESS weights, for each frequency of interest. For 13Hz, the weights are highest near the central electrodes, spread from frontal to occipital sites. Of note, RESS gave high weights to electrodes that were not selected by BE. As the SSVEP is a visual response, higher weights towards the occipital area would be expected. High weights outside of the occipital area may indicate that there is SSVEP related activity occurring throughout the scalp outside of the predefined region of interest. For 15.5Hz, weights are more pronounced towards the occipital area compared to 13Hz. The weights also seem to be focused towards the left hemisphere, as was expected. The weights obtained for the 18Hz frequency of interest seem to be distributed all over the topomap, with a concentration around the POz. A key difference between the results with BE and RESS in the attention task is that the RESS weights do not seem to follow a consistent occipital trend. The RESS weights are more distributed in various locations of the scalp compared to BE, where most frequent selections were found in the occipital region.

The distribution of weights and selected electrodes at the second harmonics were also investigated. Surprisingly, the weights and selections in the second harmonics do not resemble those of their first harmonics. Each target frequency seems to follow its own pattern, but with less concentration than in the first harmonics. This may be due to the selection being distributed among a larger number of electrodes. The RESS weights do not seem to display strong similarities between the second harmonics and the target frequencies either, with the exception of 36Hz. For BE, we also found that the second harmonics do not follow the same patterns as their respective first harmonic. This seems to suggest that the second harmonics may not be as suitable for SSVEP analysis compared to the first harmonics.

Lastly, when observing the topomaps of the timing task (Figure 2B), we can identify more consistent patterns than in the attention task across all frequencies. That is, we found that both RESS and BE primarily relied on occipital electrodes. In the timing task, the flickering circle was always in the center of the screen, and only a single flicker frequency was presented at the same time. Furthermore, the timing task mostly involves passively viewing a target at that location whereas in the attention task, the participants utilized the visual information. This may be reflected in the topomaps, as the weights and selections are mostly occipital compared to the attention task. If using temporal attention involves more activity outside of the occipital area, non-occipital activity might be prioritized over occipital activity in both RESS and BE. The timing task would not reflect any temporal attention related activity, as the task does not involve attentional selection.

Figure 3



Note: Time course of percentage change in power at the target-frequency with respect to a baseline period of 150 ms leading up to pointer onset in the attention task. Subpanels in A and B plot different methods, and colors depict the different interval conditions or methods. (A)

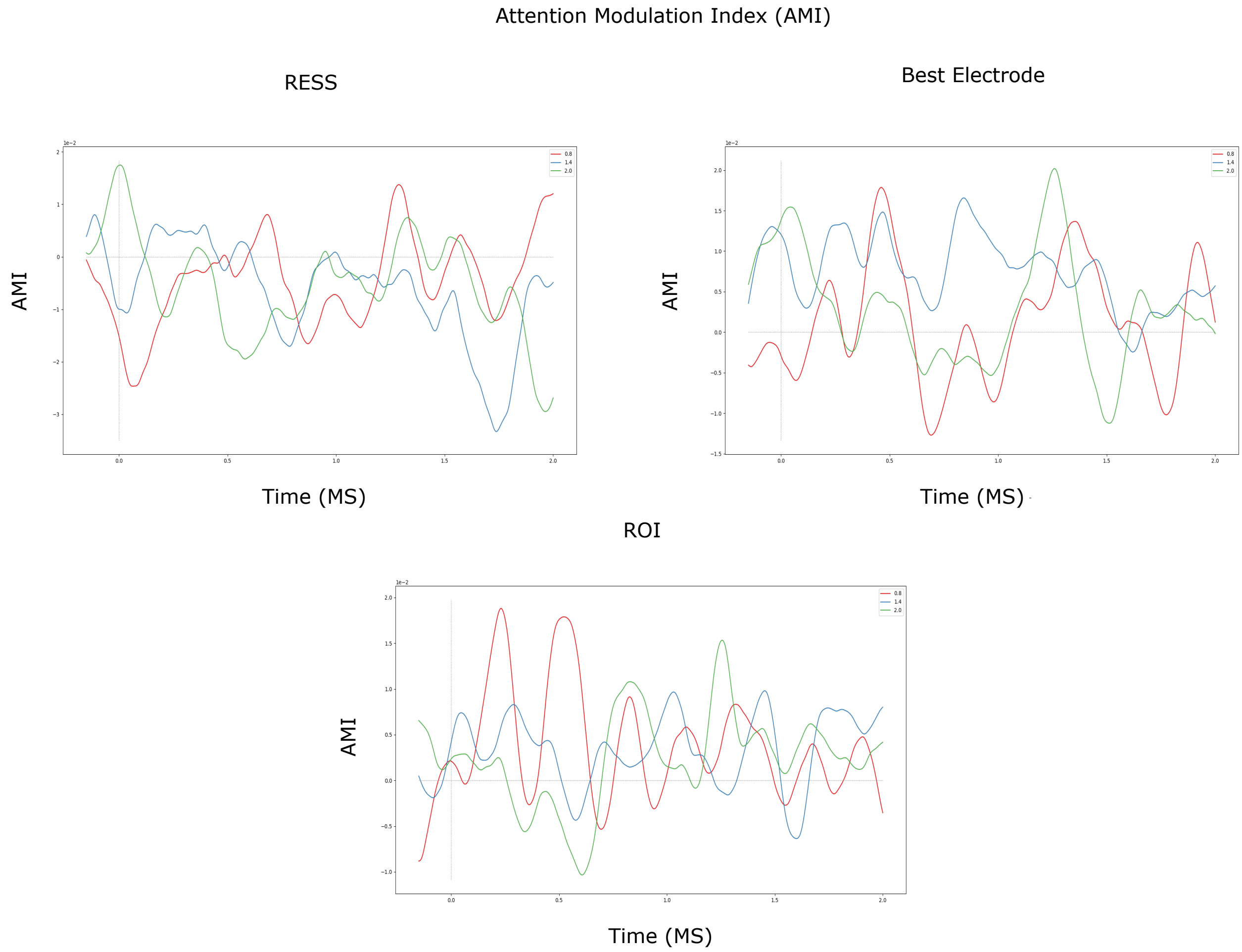
Pairwise Comparison comparing the different intervals. Bold horizontal lines reflect significant clusters. (B) Power change of target frequency amplitude. Bold horizontal lines reflect the significant clusters of the RM ANOVA. (C) Results of cluster-based RM ANOVA and Pairwise comparison of power change split on methods.

Figure 3 visualizes the power change over a 2 second interval after the presentation of the pointer. Both RM ANOVAs and a Pairwise comparisons were performed at each time point, using cluster-based permutation testing. However, this was not found for all methods or intervals. For ROI, significant clusters were found around target onset for all intervals. With BE we found significant clusters in both target onsets with the RM ANOVA, while the pairwise comparison identified a difference between the 1400ms interval and 2000ms interval from the 1554ms to 1766ms time points. we also found a significant difference between the 800ms interval and the 1400ms intervals, but not between 800ms and 2000ms intervals. With RESS we found no significant clusters with the RM ANOVA, nor with the Pairwise comparison. The timing of these significant differences, around target onset, suggest that they are related to the response more so than to temporal attention. As we see no difference in power change over time leading up to target onsets, this may indicate that timing information is not being utilized. We also looked at power change per method collapsed across the different interval conditions, and found that RESS was significantly different from both the other methods across the entire epoch, while BE and ROIs did not significantly differ at any point.

We observed that the three separate methods seem to differ in multiple ways. First, the amplitude seems to differ between the three, with RESS showing the highest amplitude between the three of them. This is not surprising, given the difference in SNR. However, high SNR might not reflect an increase in target frequency power, but a decrease in non-target frequency power. However, we did not find any significant difference between BE and ROI, which is surprising as BE is supposed to have a higher SNR by definition. Second, the amplitudes of RESS seem to have less fluctuations related to target onset compared to the other two methods. Whereas BE and ROI seem to have some decrease in power throughout the trial, RESS does not show any obvious power decreases. Lastly, the results obtained with ROI and BE show a rapid decrease followed by a similar increase in power related to the target onset. With RESS this is not as pronounced.

These differences of power change per method may suggest that the SSVEP related activity drifts throughout the scalp rather than being located specifically in the occipital region. RESS assigns weights to all electrodes distributed across the scalp, and would therefore be able to pick up SSVEP related activity in other electrodes, as can be observed in Figure 2B. If SSVEP related activity drifts, this could also explain why the power decreases over the course of the trial in the methods that primarily reflect activity in occipital electrodes.

Figure 4



Note: Figure three shows the attention modulation index (AMI) over the time course of 2000ms. AMI is the attended frequency power divided by unattended frequency power minus one, computed at each time point. The different colors depict different interval conditions (Red: 800ms, Blue: 100ms, Green: 2000ms).

Next, we computed an Attention Modulation Index (AMI, Vieweg & Müller, 2020). Rather than illustrating how SSVEP power evolves over the course of the trial, the AMI captures how power on 'attended' trials relates to power on 'unattended trials'. This AMI is computed within frequency, separately for the different interval conditions, defined as the power measured on individual trials where the frequency of interest overlapped with the upcoming target, divided by the average power observed on trials where it did not. Although positive values are observed, no significant clusters were identified, neither in the RM-

ANOVA, nor in a 1-sample t test. This indicates that the AMI is neither different from zero at any of the intervals, nor does it differ significantly between interval conditions at any point during the trial. Specifically, this means that we found no evidence of an attention-based modulation of SSVEP amplitude.

Although the AMI displayed no significant deviations from zero nor differences across conditions, some trends can be identified. Especially with ROI, the AMI seems to be higher for the shorter intervals. This could indicate that attentional shifts in this task were not marked by a sustained power modulation but by a transient response. A transient response would not necessarily occur at a specific, fixed time point of the trial. As such, we would not observe any clear markers in the grand average, but we would observe higher power overall early on in the trial for shorter intervals than for longer intervals. To an extent, the same pattern is observed with BE, but RESS forms an exception here as no discernible pattern is observed there. This may indicate that the transient response could be an effect localized at occipital sites, which is obscured in RESS which reflects activity weighted across multiple non-occipital electrodes. However, given that no significant differences in attention modulation were found between the methods we have no evidence to support whether RESS is a better or worse tool for measuring temporal attention modulation than the other methods.

Discussion

In the present study, we attempted to track the dynamics of temporal attention using SSVEP. We also compared three methods of SSVEP analysis to investigate whether RESS is a better method for tracking temporal attention through time. Specifically, we compared RESS, a BE selection method, and an ROI selection method. We used a temporal attention task where participants had to direct attention between targets flickering at different frequencies. We found that RESS produced significantly higher SNR and frequency power over time than more conventional methods. However, we found no direct evidence that temporal information was used to modulate attention over time, instead we found an increase in amplitude for the target frequency after pointer onset. Lastly, we could not find any difference in attention modulation between RESS and the other methods.

Higher SNR in RESS might be an indication that SSVEP modulations related to temporal attention are not purely an occipital effect, but rather an effect that can be found throughout the scalp. As the RESS weights were distributed throughout the scalp across a variety of areas, there is a chance that it picked up these non-occipital SSVEP related signals more consistently compared to other methods. ROI and BE mostly pick up sensory signals from the occipital region, whereas RESS may be picking up more signals related to networks related to the processing of visual attention (Fiebelkorn & Kastner, 2020). It has previously been found that when participants performed an attention task, sensory areas that process task-relevant information are coupled to networks such as the frontal-parietal network, while areas related to non-task relevant visual information gets coupled to with default-mode-network (Chadick & Gazzaley, 2011). The RESS weights might reflect how sensory information related to the flickering stimulus are activating a larger functional network for attention which would explain the more widely distributed RESS weights. If these functional networks are related to attention or temporal attention, it would also explain the discrepancy between the weight distributions of the timing task and attention task, as the timing task did not require temporal attention.

Despite an increase in task-related frequency power, no evidence for attention modulation was discovered with any of the methods. This is surprising, as this indicates that the SSVEP of each frequency did not differ between when it was attended or unattended. These findings are not in line with previous studies, which successfully found an attention modulation effect using SSVEP (Toffanin et al, 2009; Vieweg & Müller, 2020). Although these studies have investigated attention over time, no study has actually investigated the time-course of temporal attention. Another possible difference is the investigated frequencies. It is still debated which frequencies and harmonics are best to use when studying SSVEP. We chose to look at these frequencies based on Vieweg and Müller (2020) who used 16Hz and 18Hz and added 13Hz as our paradigm required a third frequency, and any frequency up to 20Hz should be viable for SSVEP attention analysis (Ding et al., 2006). We also chose to analyze the second harmonics, as Mora-Cortes and colleagues (2017) found a power increase that were potentially related to temporal expectations in the second harmonics. It has been suggested that first and second harmonics have different functional roles, where the first harmonics are not modulated by attention, while second harmonics are (Mahajan et al., 2021). However, we found that the second harmonics provided less sensible results compared to the first harmonics. This is in line with Belmonte (1998) who suggested that second harmonics only have better SSVEP transfer functions than first harmonics at frequencies of about 6Hz and lower. Therefore, it could be that we did not find any meaningful results from the second harmonics because we looked at frequencies that are too high.

The lack of significant attention modulation may be explained by the possibility that attention effects on the SSVEP are transient rather than sustained. If directing temporal attention is reflected in a transient response that can occur at any time during the trial interval, our paradigm might not be able to significantly detect such a response when assessing the grand average across participants. In our results, the transient response would be reflected by higher attention modulation during shorter trials because there would be less time for the response to occur, thus they would be more likely to occur within the same time frame. It could also be inferred that the transient response would mostly be visible in the occipital channels, as it is not pronounced in RESS, while being most visible in ROI. Previous studies have measured attention as an effect of increase in frequency power both when looking at specific occipital electrodes, and when looking at electrodes distributed all throughout the scalp (Toffanin et al., 2009; Ding et al., 2006). As the transient response could result in higher power, this would be in line with our findings. However, as few studies have looked at attention modulation over time we would not know how such power changes evolve over time. Vieweg and Müller (2020) did find a sustained attention modulation, but in their paradigm, it is likely that participants switched attention multiple times over the course of a trial. If attention indeed manifests as a transient response in the SSVEP, frequent shifting of attention could lead to multiple transient responses during a single trial giving the impression of a sustained modulation. A similar phenomenon might hold for an experiment performed by Antonov and colleagues (2020) who found a sustained attention modulation persisting for 5 seconds. This time course involved a stream of changing stimuli to attend, therefore repeated attention shifts were required. However, in the case of our task, only one attentional shift is required, and it might be the case that this shift may occur at any time before the target onset.

We found that the three methods we investigated all differed on several different aspects of SSVEP results. We found that the three methods differed not only in power, but also how power changed throughout the course of a trial. ROI and BE both showed that power gradually decreased, while RESS showed activity sustained at the same level. They also differ in that ROI and BE both reflect oscillatory power mostly at occipital electrodes, whereas the RESS weights were distributed in a variety of electrodes outside of occipital areas as well. As such, we postulate that there might be a drifting SSVEP signal over time that is not localized to occipital sites. The difference in power change could be due to RESS picking up the signal as it drifts away from occipital sites, while ROI and BE can only pick up the signal while it is in the occipital area. As the RESS topomaps also revealed the possible connectivity of functional attentional networks (see above), it may indicate that such a drift is caused by the involvement of the aforementioned functional attentional networks. Drifts of signals have also been found in ERPs, where the time point of amplitude increases was different in posterior and frontal areas (Nobre et al., 2000). Methods that exclusively focus on occipital electrodes would in this case conclude that amplitude overall decreased, rather than drifting to frontal sites. Our results would not be the first to challenge the dominant notion of a concept due to RESS findings. For example, Zuure and colleagues (2020) used RESS to demix the signals from a single area to investigate midfrontal theta oscillations, and found new properties that were not visible with other methods due to signal mixing. They found that midfrontal theta was composed of multiple distinct sources fluctuating independently, rather than only one source. In our case, we used RESS to accurately measure the SSVEP hypothesized to stem from a single area, but found evidence to suggest the signal was distributed across multiple sites.

We explored the differences between three methods of SSVEP analyses, in order to assess whether RESS is a suitable tool to measure temporal attention compared to ROI and BE. The use of RESS is often justified by the higher SNR (Cohen & Gulbinaite, 2017; Mora-Cortes et al., 2017; Gulbinaite et al., 2017). Despite the higher SNR, we did not find any evidence suggesting RESS to be a useful tool to study temporal attention modulation through time. Instead, we found all three methods to be suitable for different purposes. Our results suggest that the method used for EEG analysis should be selected based on what one would want to investigate. With ROI and BE we observed large power changes around the target onset related to the response, whereas RESS did not pick up these changes to the same extent. Conversely, RESS produced the highest SNR and power change out of the three methods. Although RESS was able to increase the SNR and power at frequencies of interest, it did so by combining over signal measured at different sites. In other words, it seems as RESS may lack spatial specificity. Therefore, if scalp location is an important aspect of a research question, RESS would not be an ideal choice for analysis. Importance of scalp location is the reason why some studies opt to select 'best' electrodes with the highest SNR from within a region of interest (Fuchs et al., 2002). Thus, all three methods have advantages and disadvantages, and choosing which to use must be done with care.

Due to the findings of the current study, we suggest that future studies better investigate both RESS and attention modulation. Given all the nuances of RESS, more studies into the method might be of interest. To our knowledge, no one has attempted to apply a partial RESS, i.e., applying an RESS using only data from regions of interest such as occipital electrodes, thereby increasing the spatial specificity of RESS. Using a partial RESS might be a way to keep spatial specificity, while still maximizing the SNR. Studies focused on using a partial RESS in different regions may provide independent time courses of SSVEP power in separate regions. This way, localized processes, i.e., processes in occipital or frontal scalp areas, might not obscure each other, as they are not occurring in the same analysis. It would also allow for analysis of these different processes' individual time courses. More insight into how to optimally apply RESS might lead to improved methods for EEG and SSVEP analysis. In turn, this may lead to new findings that may challenge current notions in a variety of fields, similar to what Zuure and colleagues (2020) did. As for temporal attention modulation, we found that a temporal attention shift might be reflected through a transient response rather than sustained activity. Due to our paradigm, we could not control when each subject shifted their attention. Therefore, we suggest further investigation into the dynamics of temporal attention over time using SSVEP, but via a design that allows for attentional shifts at predictable moments. This could provide insight into whether or not temporal attention is characterized by a transient response

Our results on attention modulation and temporal attention provides new insights into the possible dynamics of temporal attention. We could find no evidence of sustained SSVEP related attention modulation, which may suggest that SSVEP related responses are transient. We could not provide evidence for RESS being a better tool for temporal attention specifically, Instead, our findings demonstrate that the method chosen for electrode selection should be chosen in line with the exact research question. Future studies could focus on further investigating the dynamics of temporal attention through study designs where the timing of the attentional shift is predictable.

References

Ablin, P., Cardoso, J.-F., & Gramfort, A. (2018). Faster independent component analysis by preconditioning with Hessian approximations. *IEEE Transactions on Signal Processing*, *66*(15), 4040–4049. https://doi.org/10.1109/tsp.2018.2844203

Ales, J. M., Farzin, F., Rossion, B., & Norcia, A. M. (2012). An objective method for measuring face detection thresholds using the sweep steady-state visual evoked response. *Journal of Vision*, *12*(10), 18–18. https://doi.org/10.1167/12.10.18

Antonov, P. A., Chakravarthi, R., & Andersen, S. K. (2020). Too little, too late, and in the wrong place: Alpha band activity does not reflect an active mechanism of selective attention. *NeuroImage*, *219*, 117006. https://doi.org/10.1016/j.neuroimage.2020.117006

Babiloni, C., Miniussi, C., Babiloni, F., Carducci, F., Cincotti, F., Del Percio, C., Sirello, G., Fracassi, C., Nobre, A. C., & Rossini, P. M. (2004). Sub-second "temporal attention" modulates alpha rhythms. A high-resolution EEG study. *Cognitive Brain Research*, *19*(3), 259–268. https://doi.org/10.1016/j.cogbrainres.2003.12.010

Belmonte, M. (1998). Shifts of visual spatial attention modulate a steady-state visual evoked potential. *Cognitive Brain Research*, *6*(4), 295–307. https://doi.org/10.1016/s0926-6410(98)00007-x

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.-M., & Robbins, K. A. (2015). The prep pipeline: Standardized preprocessing for large-scale eeg analysis. Frontiers in Neuroinformatics, 9. https://doi.org/10.3389/fninf.2015.00016

Bundesen, C., Habekost, T., & Kyllingsbæk, S. (2011). A neural theory of visual attention and short-term memory (NTVA). *Neuropsychologia*, *49*(6), 1446–1457. https://doi.org/10.1016/j.neuropsychologia.2010.12.006

Chadick, J. Z., & Gazzaley, A. (2011). Differential coupling of visual cortex with default or frontal-parietal network based on goals. *Nature Neuroscience*, *14*(7), 830–832. https://doi.org/10.1038/nn.2823

Cohen, M. X., & Gulbinaite, R. (2017). Rhythmic entrainment source separation: Optimizing analyses of neural responses to rhythmic sensory stimulation. *NeuroImage*, *147*, 43–56. https://doi.org/10.1016/j.neuroimage.2016.11.036

Ding, J., Sperling, G., & Srinivasan, R. (2006). Attentional modulation of SSVEP power depends on the network tagged by the flicker frequency. *Cerebral Cortex*, *16*(7), 1016–1029. https://doi.org/10.1093/cercor/bhj044

Fiebelkorn, I. C., & Kastner, S. (2020). Functional specialization in the attention network. *Annual Review of Psychology*, *71*(1), 221–249. https://doi.org/10.1146/annurev-psych-010418-103429

Fuchs, M., Kastner, J., Wagner, M., Hawes, S., & Ebersole, J. S. (2002). A standardized boundary element method volume conductor model. *Clinical Neurophysiology*, *113*(5), 702–712. https://doi.org/10.1016/s1388-2457(02)00030-5

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). Meg and eeg data analysis with mne-python. Frontiers in Neuroscience, 7. https://doi.org/10.3389/fnins.2013.00267

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Parkkonen, L., & Hämäläinen, M. S. (2014). Mne software for processing meg and eeg data. NeuroImage, 86, 446–460. https://doi.org/10.1016/j.neuroimage.2013.10.027

Gruber, W. R., Zauner, A., Lechinger, J., Schabus, M., Kutil, R., & Klimesch, W. (2014). Alpha phase, temporal attention, and the generation of early event related potentials. *NeuroImage*, *103*, 119–129. https://doi.org/10.1016/j.neuroimage.2014.08.055

Gulbinaite, R., van Viegen, T., Wieling, M., Cohen, M. X., & VanRullen, R. (2017). Individual alpha peak frequency predicts 10 Hz flicker effects on selective attention. https://doi.org/10.1101/185132

Jas, M., Engemann, D. A., Bekhti, Y., Raimondo, F., & Gramfort, A. (2017). Autoreject: Automated artifact rejection for meg and eeg data. NeuroImage, 159, 417–429. https://doi.org/10.1016/j.neuroimage.2017.06.030

Lockhofen, D. E., & Mulert, C. (2021). Neurochemistry of visual attention. *Frontiers in Neuroscience*, *15*. https://doi.org/10.3389/fnins.2021.643597

Lopez-Calderon, J., & Luck, S. J. (2014). Erplab: An open-source toolbox for the analysis of event-related potentials. Frontiers in Human Neuroscience, 8. https://doi.org/10.3389/fnhum.2014.00213

Mahajan, Y., Ching, A., Watson, T., Kim, J., & Davis, C. (2021). Effect of sustained selective attention on steady-state visual evoked potentials. *Experimental Brain Research*, *240*(1), 249–261. https://doi.org/10.1007/s00221-021-06251-0

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). Opensesame: An open-source, graphical experiment builder for the social sciences. Behavior Research Methods, 44 (2), 314-324. https://doi.org/10.3758/s13428-011-0168-7

Meese, T. S. (1995). Using the standard staircase to measure the point of subjective equality: A guide based on computer simulations. *Perception & Psychophysics*, *57*(3), 267–281. https://doi.org/10.3758/bf03213053

Min, B.-K., Park, J. Y., Kim, E. J., Kim, J. I., Kim, J.-J., & Park, H.-J. (2008). Prestimulus EEG alpha activity reflects temporal expectancy. *Neuroscience Letters*, *438*(3), 270–274. https://doi.org/10.1016/j.neulet.2008.04.067

Mora-Cortes, A., Ridderinkhof, K. R., & Cohen, M. X. (2017). Evaluating the feasibility of the steady-state visual evoked potential (SSVEP) to study temporal attention. *Psychophysiology*, *55*(5). https://doi.org/10.1111/psyp.13029

Muthukumaraswamy, S. (2013). High-frequency brain activity and muscle artifacts in meg/eeg: A review and recommendations. Frontiers in Human Neuroscience, 7. https://doi.org/10.3389/fnhum.2013.00138

Nobre, A. C., Sebestyen, G. N., & Miniussi, C. (2000). The dynamics of shifting visuospatial attention revealed by event-related potentials. *Neuropsychologia*, *38*(7), 964–974. https://doi.org/10.1016/s0028-3932(00)00015-4

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J.-M. (2011). Fieldtrip: Open source software for advanced analysis of meg, eeg, and invasive electrophysiological data. Computational Intelligence and Neuroscience, 2011, 1–9. https://doi.org/10.1155/2011/156869

Peirce, J. W. (2007). Psychopy-psychophysics software in python. Journal of Neuroscience Methods, 162 (1-2), 8–13. https://doi.org/10.1016/j.jneumeth.2006.11.017

Phyo Wai, A. A., Lee, J. C., Yang, T., So, R., & Guan, C. (2020). Effects of stimulus spatial resolution on SSVEP responses under overt and covert attention. *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. https://doi.org/10.1109/embc44109.2020.9176678

Rohenkohl, G., Cravo, A. M., Wyart, V., & Nobre, A. C. (2012). Temporal expectation improves the quality of sensory information. *Journal of Neuroscience*, *32*(24), 8424–8428. https://doi.org/10.1523/jneurosci.0804-12.2012

Rolke, B., Festl, F., & Seibold, V. C. (2016). Toward the influence of temporal attention on the selection of targets in a visual search task: An ERP study. *Psychophysiology*, *53*(11), 1690–1701. https://doi.org/10.1111/psyp.12734

Sanchez-Lopez, J., Pedersini, C. A., Di Russo, F., Cardobi, N., Fonte, C., Varalta, V., Prior, M., Smania, N., Savazzi, S., & Marzi, C. A. (2019). Visually evoked responses from the blind field of Hemianopic Patients. *Neuropsychologia*, *128*, 127–139. https://doi.org/10.1016/j.neuropsychologia.2017.10.008

Toffanin, P., de Jong, R., Johnson, A., & Martens, S. (2009). Using frequency tagging to quantify attentional deployment in a visual divided attention task. *International Journal of Psychophysiology*, *72*(3), 289–298. https://doi.org/10.1016/j.ijpsycho.2009.01.006

Tsotsos, J. K., Culhane, S. M., Kei Wai, W. Y., Lai, Y., Davis, N., & Nuflo, F. (1995). Modeling visual attention via selective tuning. *Artificial Intelligence*, *78*(1-2), 507–545. https://doi.org/10.1016/0004-3702(95)00025-9

Vieweg, P., & Müller, M. M. (2021). Shifting attention in feature space: Fast facilitation of the to-be-attended feature is followed by slow inhibition of the to-be-ignored feature. *Journal of Cognitive Neuroscience*, *33*(4), 651–661. https://doi.org/10.1162/jocn_a_01669

Vissers, M. E., Gulbinaite, R., van den Bos, T., & Slagter, H. A. (2017). Protecting visual short-term memory during maintenance: Attentional modulation of target and distractor representations. *Scientific Reports*, *7*(1). https://doi.org/10.1038/s41598-017-03995-0

Zuure, M. B., Hinkley, L. B., Tiesinga, P. H. E., Nagarajan, S. S., & Cohen, M. X. (2020). Multiple midfrontal thetas revealed by source separation of simultaneous MEG and EEG. *The Journal of Neuroscience*, *40*(40), 7702–7713. https://doi.org/10.1523/jneurosci.0321-20.2020