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Research Article

Keywords: event-related, performance, brain-computer interface, P300 BCI

Posted Date: April 12th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-380982/v1>

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Difference in somatosensory event-related potentials in the blind subjects leads to better performance in tactile P300 BCI

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ABSTRACT

In this study, we created 8-command P300 tactile brain-computer interface, running on minimally modified consumer Braille display, and tested it on 10 blind subjects and 10 sighted controls with two stimuli types, differing in size. Larger stimuli provide better BCI performance both in blind and sighted participants than smaller stimuli. With large stimuli, median target selection accuracy in the blind group was 95%, which is 27% more than sighted controls ($p < 0.05$), suggesting that blind subjects are not only able to use tactile brain-computer interface but also can achieve superior results in comparison with sighted subjects. The difference in event-related potentials between groups is located in frontocentral sites around 300 ms post-stimulus and corresponds with early cognitive event-related potential components. Blind subjects have higher amplitude and shorter latency of ERPs. This effect was consistent across stimuli types. This is the first study to evaluate differences in event-related potentials between blind and sighted subjects in a BCI-specific task.

Introduction

Noninvasive brain-computer interfaces (BCIs) are rapidly developing as assistive technology for people with severe clinical disorders. Nowadays BCI is routinely used for communication in disabled patients as well as for controlling external devices such as robots and virtual environments. Most widespread communicative BCIs employ paradigms based on various visual evoked potentials, including P300 event-related potential (ERP), steady-state visual evoked potentials (SSVEP), and code-modulated visual evoked potentials (C-VEP). The subjects are supposed to direct their attention to the target of interest, which is activated in a manner to generate event-related potentials, that are classified to form a command to the computer. Visual P300 ERP paradigm is probably the most popular, being featured in various commercial products, enabling communication in patients who are unable to speak or move¹. It is based on the effect that an unlikely event induces the P300 component in the EEG. Most visual P300 BCI implementations rely on the direction of eye gaze and can't be used by patients, who are not able to voluntarily control eye movement. However, the solutions for this problem are being proposed, with gaze-independent spellers based on rapid serial visual presentation^{2,3}. On the other hand, patients with severely impaired or absent vision are not able to use most visual BCIs, creating a need for other sensory modalities, such as auditory and tactile.

While there is a large body of research regarding the influence of stimulation parameters on visual BCI performance, this is still lacking for tactile BCI. Braille displays allow to change tactile patterns used for stimulation, allowing to test whether some stimuli parameters (linear size, timing, or amplitude) are better than others for BCI.

Tactile BCIs are not as well-studied as visual ones and usually require to use custom stimulation device. There are several options in the design of tactile stimulators. One possible stimulation modality for tactile P300 BCI is electrical stimulation. There has been a report of P300 BCI, based on selective attention to one of the four fingers being electrically stimulated with FES device⁴. Another option is mechanical stimulation, for example, vibration motors⁵. Powerful linear tactors, primarily used for haptic feedback vests, can provide powerful haptic pulse⁶, helping more reliable recognition of stimulation. It's also possible to use refreshable Braille cells, assembled as a custom device^{7,8}. However, readily available multicell Braille displays were not used as tactile stimulators in BCI yet, though using minimally modified commercial hardware can significantly simplify the experimental setup of the study.

Tactile BCI usually have lower accuracy and speed than visual ones. This was demonstrated in⁷, where subjects were able to achieve near 100% target selection accuracy in visual P300 speller, while their accuracy in tactile P300 BCI never exceeded 80%. However, more recent studies⁶ report subjects achieving accuracy over 95%, being able to control a wheelchair. The case of successfully decoding evoked potentials, produced by stimulation of a single finger with two different tactile patterns, generated by Braille cells, was also reported, with accuracy getting as high as 90%^{8,9}.

The common feature of the abovementioned BCI studies is the demography of the participants, being mostly healthy volunteers. This imbalance in BCI research has been discussed for a long time⁶. Most subjects in the research are either students or faculty staff, with no obvious health problems. While there is a case of testing tactile BCI with subjects, suffering some levels of visual impairment¹⁰, the studies focusing on neurophysiological differences between the blind and the sighted group are yet to be performed.

The main practical goal of the recent BCI development is to accommodate the individual needs of paralysed patients. While generally visual BCIs can be used by such patients, visual disability or complete vision loss can limit BCIs to tactile and auditory modalities. This justifies the importance of evaluating tactile BCI performance in subjects suffering long-term vision loss.

Blindness offers unique opportunities to study the phenomenon of neuroplasticity, more specifically, how sensory experience influences the functional and anatomical properties of the brain. Cortical areas can be significantly reorganized in subjects, suffering long-term vision loss¹¹. Although sensory compensation in the blind is considered a well-established phenomenon¹², the extent of behavioral and neurophysiological differences between blind and sighted cohorts is still subject to discussion. For example, blind subjects are shown to perform better in the grating orientation task¹³ and recently in a texture discrimination task with¹⁴. However, some previous studies have failed to find differences between blind and sighted groups in tactile tests^{15,16}, including aforementioned¹⁴, where groups did not differ in a shape discrimination task.

It still remains to be clarified, whether Braille reading proficiency is correlated with tactile acuity and how this connection can be captured in different tactile tests and experimental paradigms. There were reports of blind Braille readers being not better in tactile tests than blind non-readers¹⁶. Some reports even propose that Braille readers are worse in some tasks, for example¹⁷, where blind Braille readers were mislocating stimuli between hands and fingers more often than non-readers. On the other hand, tactile acuity is increased by practice, for example in musicians¹⁸, and experienced Braille readers do have several hours of relevant tactile practice every day.

In order to extend this body of research, in this study we have designed tactile P300 BCI setup, running on commercially available Braille display, and tested it with the blind and the sighted subjects to answer three research questions. First, whether blind subjects perform tactile BCI tasks better than sighted subjects. Secondly, whether there are differences in neurophysiological responses to tactile stimulation between blind and sighted subjects. Third, whether there are differences in P300 response and BCI performance with large and small Braille stimuli.

Methods

Subjects

Eleven peripherally blind and ten sighted participants took part in the experiment. One blind subject was excluded from analysis due to revealed medical condition, resulting in a high difference in tactile acuity between hands. In the remaining group 5 blind subjects were congenitally blind, and 5 have been suffering vision loss for at least 8 years. 3 subjects had residual light sensitivity. Blind subjects were Braille-literate. There were 3 men and 7 women in the blind group (age range 20-52 years, mean 35 years) and 6 men and 4 women in the sighted group (age range 19-46 years, mean 31.3 years). All sighted subjects had normal or corrected-to-normal vision acuity and no known history of neurological disease. The study was performed in accordance with the declaration of Helsinki and all participants gave written informed consent. The study was approved by the Research Ethics Commission of ANO "Laboratory Sensor-Tech"

Apparatus

EEG was recorded at 500 Hz sampling rate using 45 Ag/AgCl gel electrodes and NVX-52 amplifier (MKS, Zelenograd, Russia). The electrodes used were: FP1, FP2, F3, Fz, F4, FC5, FC3, FC1, FCz, FC2, FC4, FC6, T7, C5, C3, C1, Cz, C2, C4, C6, T8, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO7, PO3, POz, PO4, PO8, O1, Oz, O2, according to 10-10 electrode system. Electrodes were referenced to linked earlobes with AFz ground. Additionally, the ECG electrode was placed on the subject's right wrist.

The stimulation device consisted of unaltered commercially available 40-cell Braille display ALVA USB 640 Comfort (Optelec, Barendrecht, the Netherlands). The device was connected via Bluetooth and controlled via BrIAPI¹⁹. Three rightmost Braille cells were utilized for the custom optical synchronization device, generating TTL pulse when underlying cells switched into the activated position (see Fig. 1). Every stimuli activation that was presented to the subject was accompanied by synchronous activation of these cells and following the TTL pulse, which was detected by the EEG device and synced with the

data stream. The EEG and TTL data were streamed to the BCI application using LSL protocol²⁰. The custom BCI application was written in Python 2.7, running on Windows 8 - based laptop.



Figure 1. Subject hands positioned on the Braille display. The synchronization device is on the right.

Design and procedure

Before the experiment, subjects were required to read the text of the informed consent (around 5000 characters with spaces) in Russian. For blind subjects, the text of informed consent was embossed using a Braille printer (7 one-sided A4 pages), and the time spent on reading Braille text was measured. Also, the subjects were asked to report the average time they spend reading Braille text (hours per week).

After installing the electrodes, the subjects were seated in front of the table and placed their hands on the Braille display. To ensure comfort and accommodate different sized hands, the positions of active cells were adjusted for every participant. For sighted subjects, during the BCI sessions, the view of the Braille display was obstructed with a cardboard box. The stimulation trial consisted of randomised activation of Braille cell for 200 ms with stimulus onset asynchrony of 300 ms. The Braille pattern was the same for all cells.

One session consisted of 80 randomized activations of all 8 stimuli, each being activated 10 times. All sessions used 8 active cells, so participants needed to use 8 fingers (index, ring, the middle, and little finger on each hand). The BCI task given to the subject was to count activations under the target finger, ignoring all others. The target finger was presented to the participant before each session using tactile cue (10 fast activations of target Braille cell).

There were two experimental conditions with different stimuli sizes. The condition with large stimuli used activation of the full Braille cell (8 pins), and the condition with small stimuli used activation of a single pin at the center of the cell (pin 5) (Fig. 2). Conditions were presented in a randomised order.

Each condition consisted of 6 learning sessions (without feedback), followed by 10 sessions with BCI feedback. Learning sessions resulted in 60 target and 420 non-target EEG trials being used to train the classifier. Then, the newly trained classifier was used to deliver feedback on selected targets via voice synthesizer for 10 next sessions (after the session the subject heard the target finger number). Participants were told that the goal of the game is to get the computer to guess the correct target. Overall, the condition generated 16 sessions of data, with each finger being target 2 times. 160 target and 1120 non-target trials were used for analysis. Along with these two BCI sessions, participants optionally completed one or two other 10-15 minutes long tasks with Braille display, which are not part of this study.

Data analysis

Preprocessing

Recorded EEG was re-referenced using common average reference. Then, ICA was used to reject oculomotor artifacts. Since ICA is sensitive to low-frequency drifts, raw EEG was filtered using the 4th-order Butterworth filter from 1 to 35 Hz. Then, components, highly correlated with FP1 and FP2 channels, were rejected. The resulting unmixing matrix was applied to

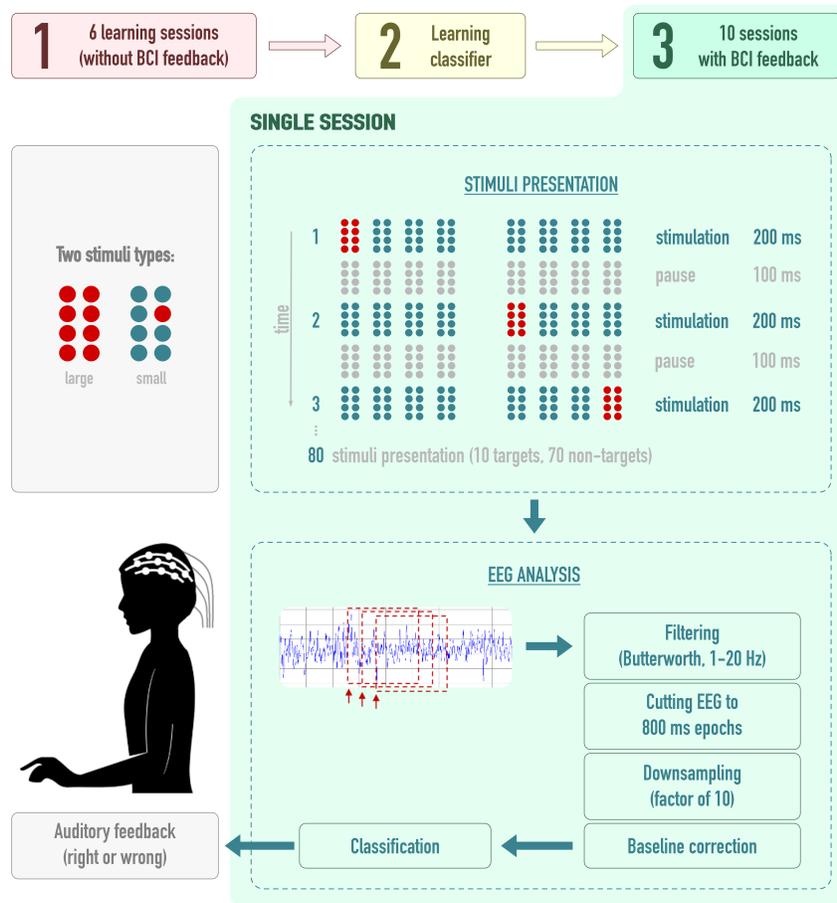


Figure 2. Experimental setup and analysis pipeline

EEG, filtered from 0.1 to 35 Hz with an additional zero-phase notch filter at 50 Hz. This way, at the cost of slightly worse oculomotor artifact subtraction, we are able to preserve more accurate ERP waveforms, which are reported to suffer from excessive high-pass filtering^{21,22}. Then, filtered EEG was cut into epochs and averaged for each stimulus within every session per participant, with average evoked potentials being baseline-corrected using 50 ms pre-stimulus.

Waveform analysis

Averaged non-target ERPs were subtracted from target ERPs for each participant, eliminating task-unrelated activity. The resulting differential ERPs were compared with non-parametric spatiotemporal cluster-based permutation test with 10000 permutations, as described in^{23,24}. F-test was used as an estimator with an adaptive cluster threshold corresponding to a 0.05 significance level. The connectivity matrix for clustering was computed using Delaunay triangulation based on 2D sensor locations. We performed the following comparisons: blind group vs sighted group, right hand vs left hand both for blind and sighted, primary reading finger vs all other fingers in the blind. ERPs were compared separately for both stimuli types (large and small).

Online classification

During the BCI experiment, the online classification was performed to provide feedback to the user. The incoming EEG was filtered with 4th-order Butterworth filter from 1 to 20 Hz., then cut into 800 ms epochs post-stimulus and downsampled by the factor of 10 with an anti-aliasing filter applied. Then, the subset of 11 channels was chosen over central and parietal areas, where P300 ERP is pronounced (C3, Cz, C4, C6, CP3, CPz, CP4, Pz, PO3, PO4) and epochs were converted into feature vectors. The channels were selected for classification prior to the experiment. Single-trial feature vectors were classified using Fisher's linear discriminant analysis with automatic Ledoit-Wolf shrinkage²⁵. The classifier returned the probability of each epoch being of the target class. Then the probabilities were aggregated by multiplication across stimuli presentations, and the highest yielding stimuli were considered to be the target.

Offline classification

To further evaluate the recorded data, the offline classification was performed. The data was preprocessed with the same pipeline that was used for waveform analysis, with 1-20 Hz filter and epochs starting at 100 ms poststimulus. Target selection accuracy was computed with 1000-times stratified shuffle split cross-validation with the same classifier core that was used in online mode. The scoring function did take into account dataset imbalance towards non-target responses and included aggregation of single-trial classification results. The resulting numbers simulate target selection accuracy for any number of stimuli presentations, with the exception of order effects in ERPs²⁶. Pairwise comparisons of offline classification accuracies were carried out with the Mann-Whitney test. Prior to comparisons, the outliers, defined as 1.5 interquartile range, were removed from comparison. For within-subject comparisons between large and small stimuli, we were using the Wilcoxon signed-rank test. Correlation coefficients were computed using the Kendall tau statistic.

Tools

All analysis steps were performed using Python 3.7. MNE-python 0.19²⁷ was used for preprocessing and analysis, and Scikit-learn package²⁸ for classification. BIDS format²⁹ was used for dataset organisation.

Code availability

The code with all analysis steps is available at https://github.com/eegdude/erp_analysis/tree/brlbci.

Results

EEG

The evoked activity in blind and sighted subjects is dominated by a P300 peak around 300-400 ms. ERPs also have positivity before P300 in frontocentral sites, peaking around 150 ms post-stimulus in blind subjects and around 300 ms in sighted (see Fig. 4 and Fig. 3). This early positive component exhibits significant differences between blind and sighted groups both in conditions with large and small stimuli.

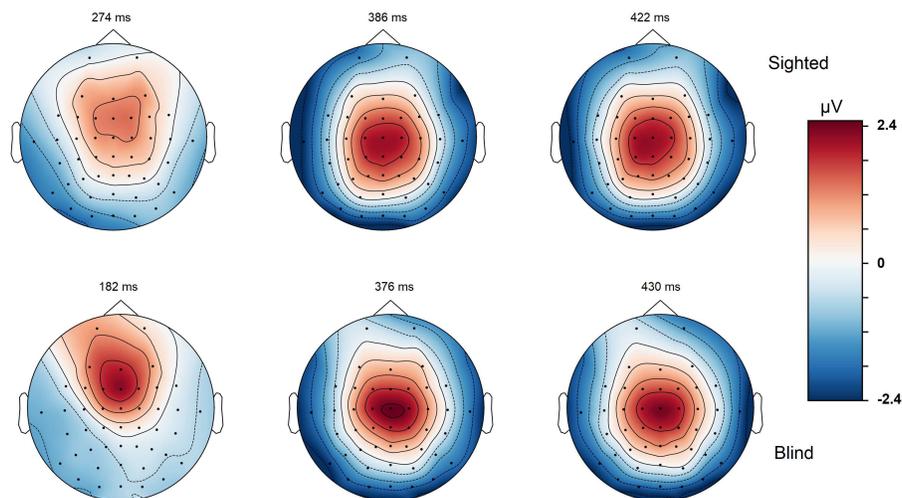


Figure 3. Topographical maps of evoked data for sighted and blind subjects at automatically detected peaks around P300.

For large stimuli, mean F-score for cluster 3.3 and $p = 0.011$. The cluster is located at central F, FC, and C electrode sites and the area of significance spans for approximately 200 ms starting around 60 ms post-stimulus. The condition with smaller stimuli demonstrates a similar effect: significant frontocentral cluster from around 120 to 300 ms with a mean F 3.55 and $p < 0.03$ (see Fig. 5 for details). Note that the existence of a significant cluster as a whole does not imply a significant difference at any specific time and site inside that cluster²⁴. No significant differences were found for differential ERPs from right and left hands, or from different fingers (including primary reading finger vs others). Non-target ERPs from the right and left hand demonstrate expected contralateral distribution (see supp. 1). Congenitally blind did not demonstrate significant ERP differences from the rest of the blind group.

Classification

For BCI with 8 commands, the chance accuracy level is 12.5%. In the experiment, accuracy in both conditions exceeded this threshold. Median offline accuracy with 10 target stimuli per session for large stimuli condition for all participants was 0.75,

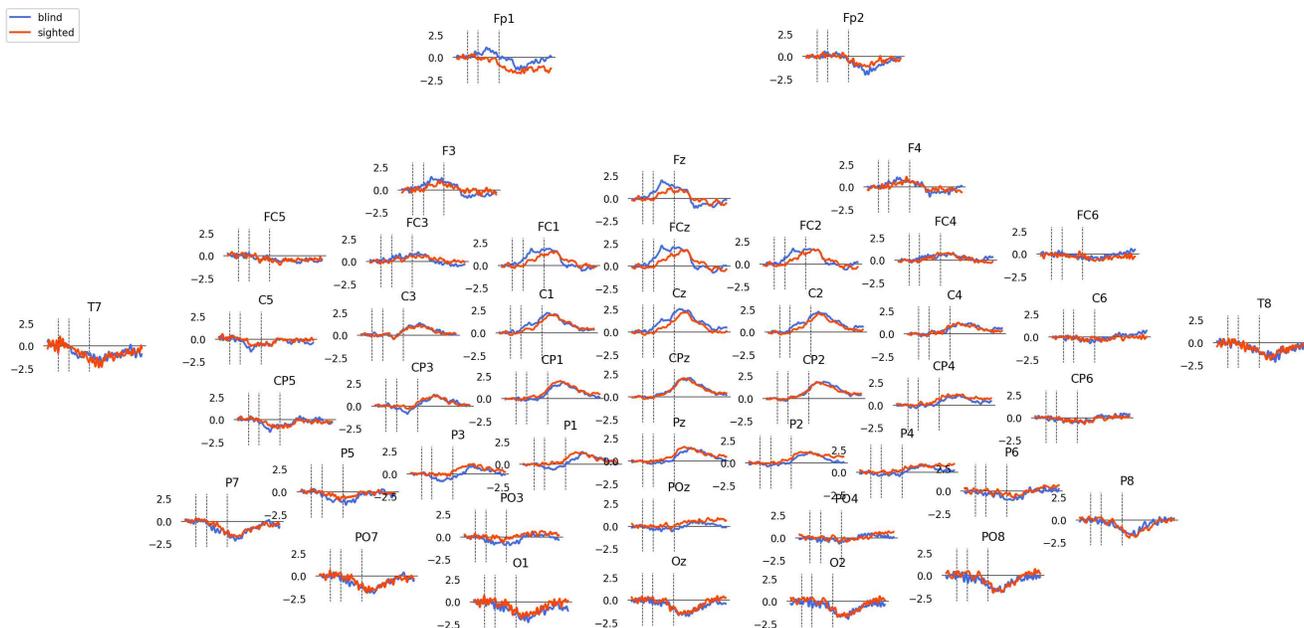


Figure 4. Between-subject grand average differential waveforms of blind and sighted subjects in condition with large stimuli. Vertical dashed lines represent 0, 100, and 300 ms post-stimulus

and 0.53 for small stimuli. The tendency of smaller stimuli yielding less is still present, when the sample is divided into blind and sighted groups: in the sighted group reconstructed accuracies for large and small stimuli were 0.62 and 0.5, and in blind group 0.95 and 0.77 correspondingly. This result was statistically significant for the combined sample (Wilcoxon $\mathcal{W} = 27$, $p = 0.0036$), for the blind group ($\mathcal{W} = 8$, $p = 0.047$), and for the sighted group ($\mathcal{W} = 6$, $p = 0.03$). It's worth noting, that despite lower classification accuracies for sighted subjects and for smaller stimuli, one of the sighted participants was still able to achieve 100% accuracy in both conditions.

Overall the performance of blind subjects was significantly better than that of sighted with large stimuli ($\mathcal{W} = 15$, $p = 0.008$) and in the combined sample ($\mathcal{W} = 15$, $p = 0.008$). For small stimuli, the difference between blind and sighted groups was not significant ($\mathcal{W} = 37$, $p = 0.17$), see Fig. 6. The classification accuracies in both stimuli conditions are highly correlated within subjects in the combined group of blind and sighted subjects ($\tau = 0.64$, $p = 3 \times 10^{-5}$) and in each subgroup: blind ($\tau = 0.5$, $p = 0.047$) and sighted ($\tau = 0.77$, $p = 0.001$, see Fig. 7A). No significant correlation was found between subject age and classification performance. The accuracy in the blind group is significantly correlated with time spent on reading the Braille text of informed consent, measured at the beginning of the experiment ($\tau = -0.47$, $p = 0.004$, see Fig. 7B). Interestingly, there is no significant correlation between informed consent reading time and self-reported daily Braille reading time, and the latter is not also correlated with ERP classification accuracy. One way to assess the validity of differences in EEG clusters described above is to check how accurate the classifier can separate one group from another by ERP waveforms. Binary classification may serve as an alternative to null hypothesis testing with fewer assumptions³⁰. Using the same classification pipeline in a pooled dataset of single-trial ERPs, we were able to classify blind from sighted by with 62% accuracy. Between-group classification accuracy greater than chance level can serve as an alternative measure of differences in ERP waveforms, that are assessed earlier with cluster-based permutation test.

Discussion

Our study allows to state that blind subjects with some level of proficiency with Braille perform differently from sighted subjects with no specific tactile training.

We have found significant differences in event-related activity between blind and sighted groups. The underlying maths of cluster-based permutation test does not allow too specific claims about the location of the effect²⁴, however, the frontocentral location of the cluster and its timing fits into the early stages of cognitive processing of the stimuli.

It has been established in the seminal paper by Sadato³¹, that the visual cortex is activated in Braille readers, with Cohen³² showing that this activation not just occurs, but also is necessary for haptic object recognition. We were not able to find

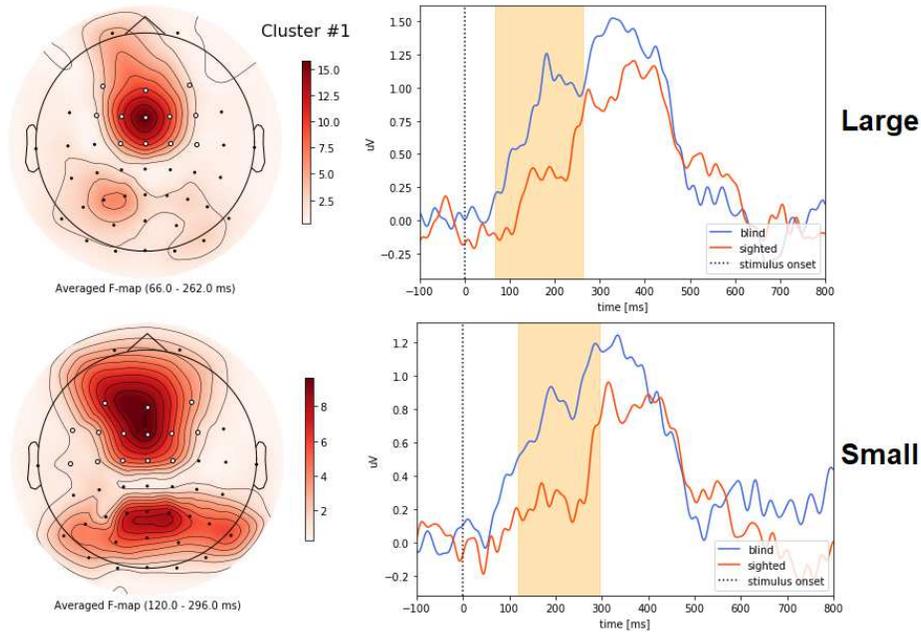


Figure 5. Significant differences between blind and sighted groups in conditions with large and small stimuli from the cluster-based permutation test. On the left is the F-score map with highlighted significant channels (white markers). On the right is the average differential waveform for the cluster. The colored area on the waveform plot corresponds to the $p < 0.05$ significance window

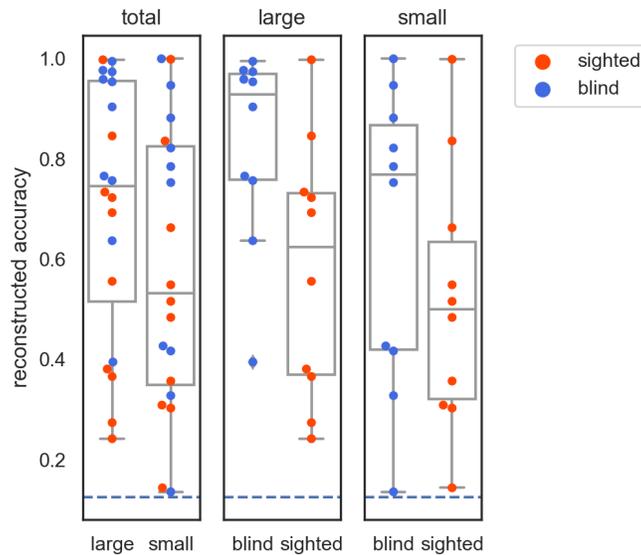


Figure 6. Reconstructed classification accuracy for all stimuli conditions (median, 25%-75% quartiles, range, data points). The dashed line represents the chance level. Diamond (◆) marker represents an outlier.

any electrophysiological markers in the occipital areas that differ between blind and sighted groups. This may be due to the specificity of the BCI task, requiring discrimination of different fingers. Previous studies have shown that visual areas are specifically activated during tasks, requiring recognition of Braille letters, but not by nonsense Braille combinations or touching reading hand³³. Recently, it has been shown that sighted subjects can experience similar cortical reorganization after mastering Braille reading³⁴.

We have not found any correlations of BCI performance with age, while it has been reported, that older subjects demonstrate inferior performance in tactile BCI³⁵, and in ERP BCI in general. No correlation was found between subject age and the time,

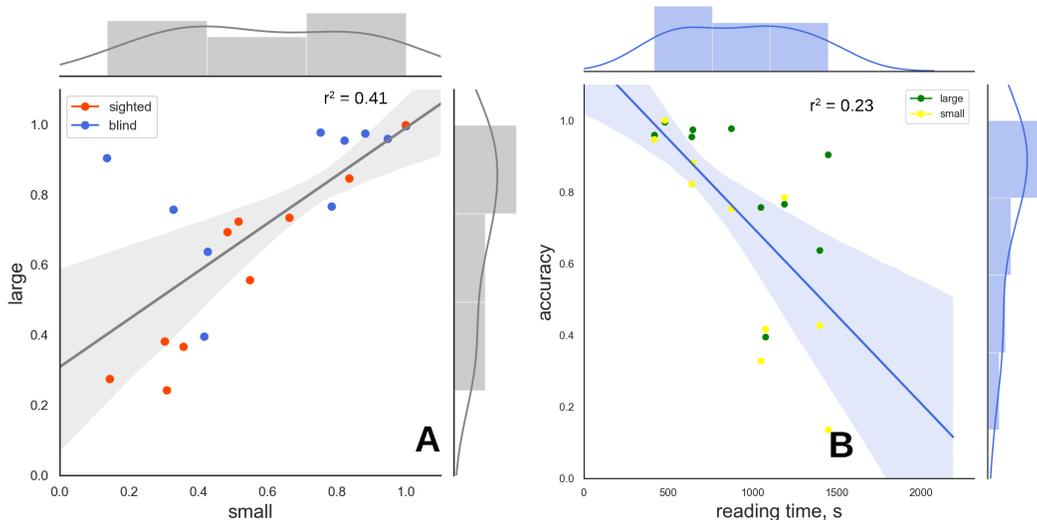


Figure 7. Correlations of classification accuracy. A - Correlation between each subject's performance in all conditions. B - Correlation between informed consent reading time and classification accuracy for blind subjects for all stimuli types.

spent on reading the informed consent Braille text.

Interestingly, in the present study, the success in the tactile Braille reading task was correlated with success in completely different tasks of finger discrimination in BCI, despite what was claimed before¹⁷. We have used both self-reported metric (daily Braille use) and Braille reading time (informed consent reading time) to assess Braille literacy. Subjective self-reported metrics suffer from various biases, so the objective metric is preferable. However, self-paced reading is probably not the best tool to measure Braille proficiency, since it depends on a number of other factors, including general reading comprehension skills and attention level, which may also influence BCI performance.

Larger amplitudes of differential ERPs in the blind group (vs sighted group) indicate larger difference between target and non-target ERPs classes and thus is directly linked to better BCI performance with linear classifier. However, ERPs depend on the level of fatigue, overall perceptual complexity of the task for the user, and cognitive workload³⁶. It's still not obvious how changes in EEG translate into changes in behavior. This is why the higher BCI performance and even higher ERP amplitude in the blind group by itself are not enough to claim higher tactile acuity without additional behavioral tests.

The current design allows to state that blind subjects with some level of proficiency with Braille perform differently from sighted subjects with no specific tactile training. The study demonstrates that blind subjects are able to achieve high performance in BCI-specific tactile task.

Also, we have assessed tactile BCI performance with two different size of stimuli. Lower classification accuracy in both groups in the condition with small stimuli can at least partially be addressed to subjects temporarily losing the target cell, as well as the characteristics of stimuli itself. Further evaluation of the effect on the size of stimuli may require a device with the fixed relative position of finger and Braille cell. Another option is to analyze kinematic data, tracking fingers during natural reading, a paradigm being used to study language processing in the blind. Participants did frequently report that some Braille letters are easier to discriminate between than others, with reasons involving the size of the letter.

Further investigation is needed, with more focus on the connection between sensory experience, Braille literacy, and performance in different haptic tests. Future studies on the subject also may benefit from dedicated tactile acuity testing and prior training of subjects.

Conclusion

This is the first study to evaluate differences between the blind and the sighted in both tactile BCI performance and ERP components in a BCI-specific task. We demonstrated significant differences in early cognitive ERPs between blind and sighted cohorts and higher classification accuracy in blind subjects. Additional research would be needed to establish the mechanisms under the differences in tactile perception not only between blind and sighted groups but also inside the blind group. A positive correlation between BCI performance and Braille proficiency opens a question for new research regarding the causation of the effect.

Data availability

The datasets generated during and analysed during the current study are available in the GIN repository <https://gin.g-node.org>, DOI: [10.12751/g-node.dyby2g](https://doi.org/10.12751/g-node.dyby2g).

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Acknowledgements

Authors thank the «Con-nection» Deaf-Blind Support Foundation for the help with recruitment of blind subjects. Authors also thank Alexander Toroptsev and Svetlana Kim for the help with conducting experiments, Dr. Seung-Goo Kim and Anna Vasilevskaya for valuable comments, and Daniil Kuznetsov for language editing.

Author contributions statement

R.G., D.G., A.D., A.K. and D.K conceived and conceptualised the experiment, R.G., D.G. and K.R. conducted the experiment, R.G analysed the results, R.G., D.G., A.D., and D.K. wrote the article. All authors reviewed the manuscript.

Additional information

Competing interests: The authors declare no competing interests.

Figures

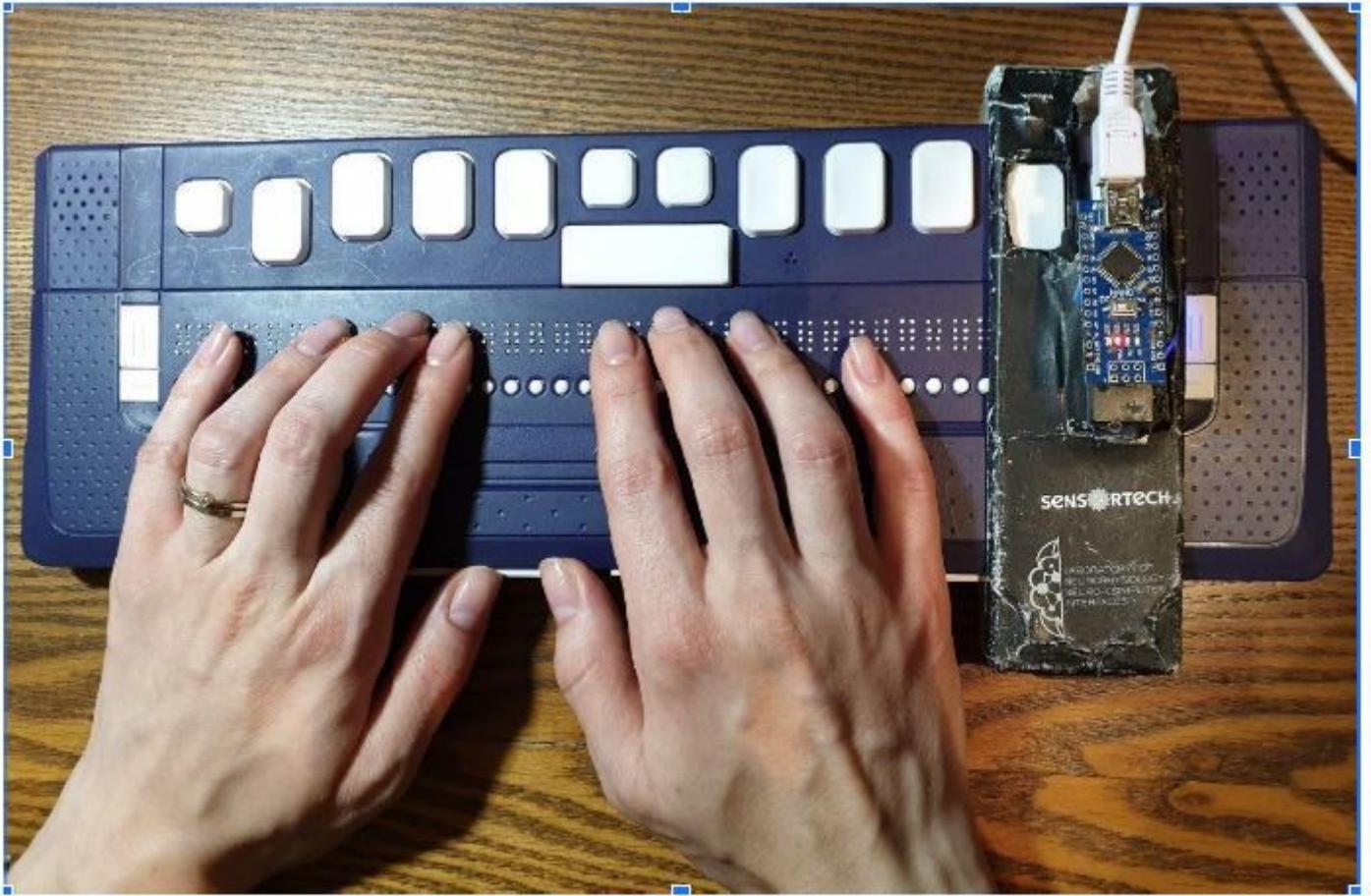


Figure 1

Subject hands positioned on the Braille display. The synchronization device is on the right.

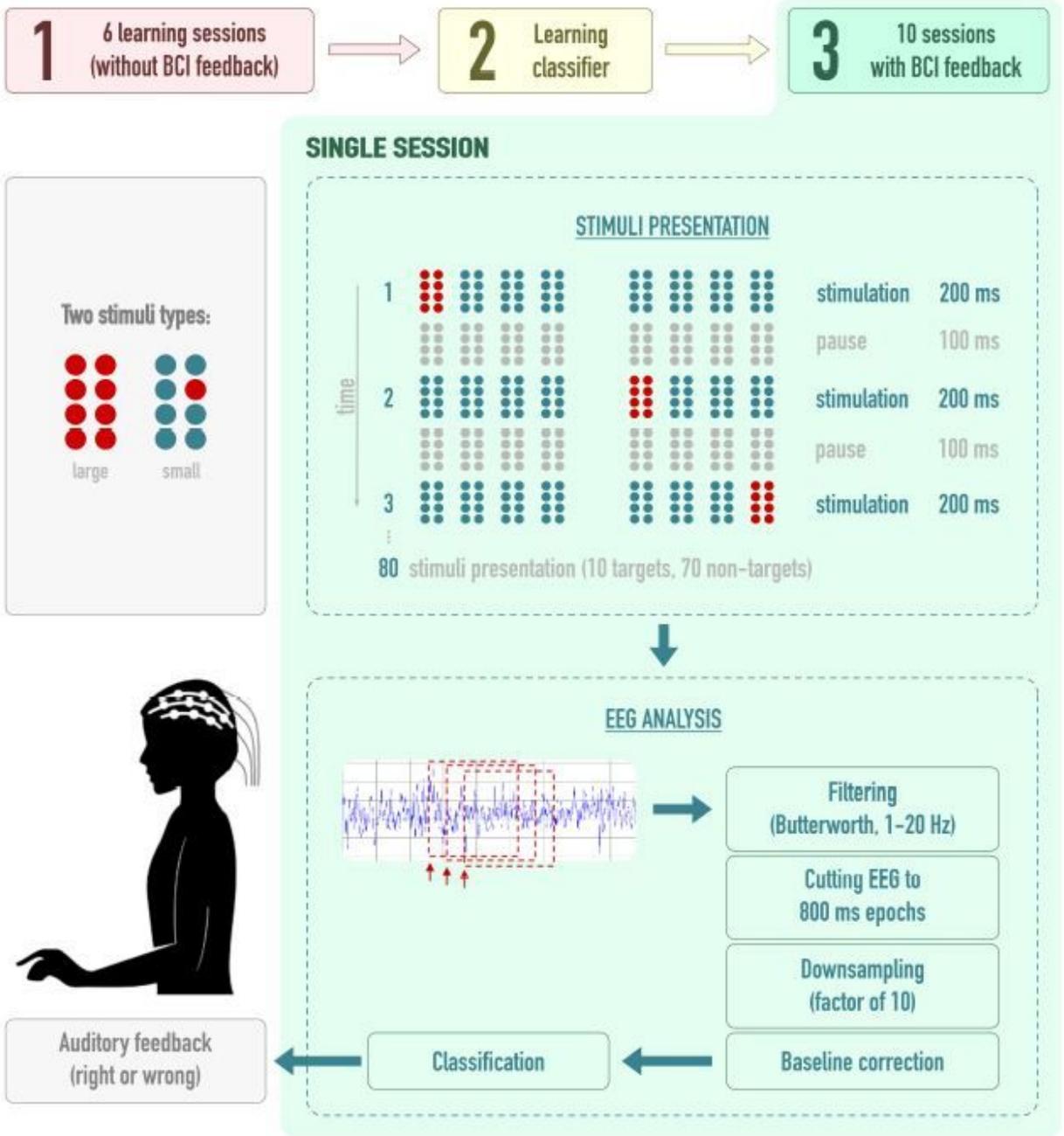


Figure 2

Experimental setup and analysis pipeline

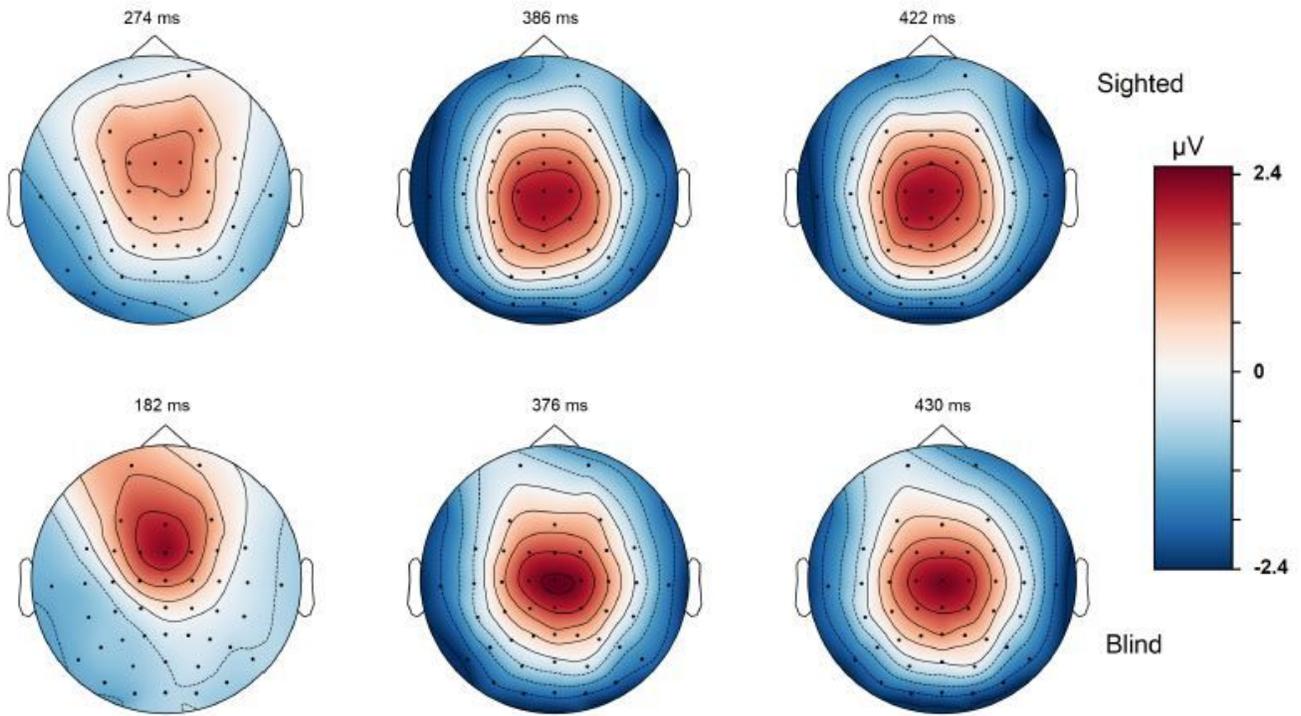


Figure 3

Topographical maps of evoked data for sighted and blind subjects at automatically detected peaks around P300.

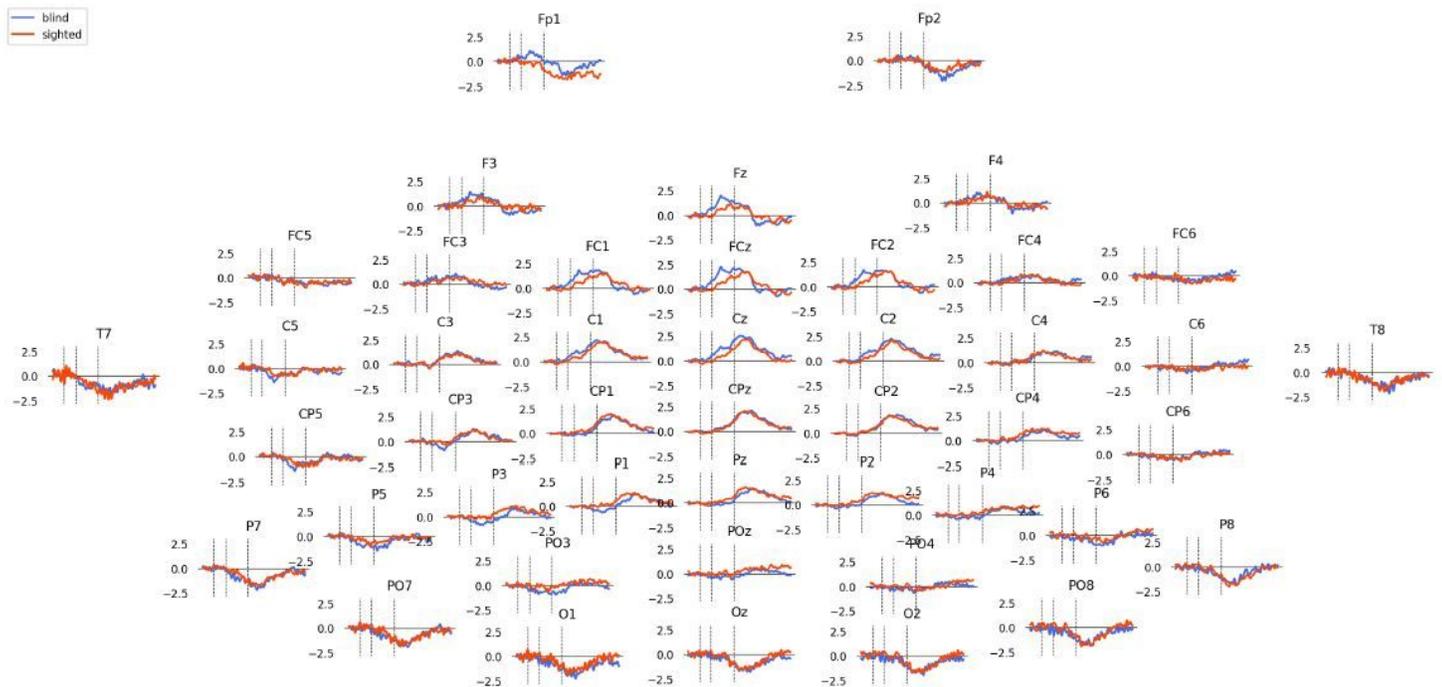


Figure 4

Between-subject grand average differential waveforms of blind and sighted subjects in condition with large stimuli. Vertical dashed lines represent 0, 100, and 300 ms post-stimulus

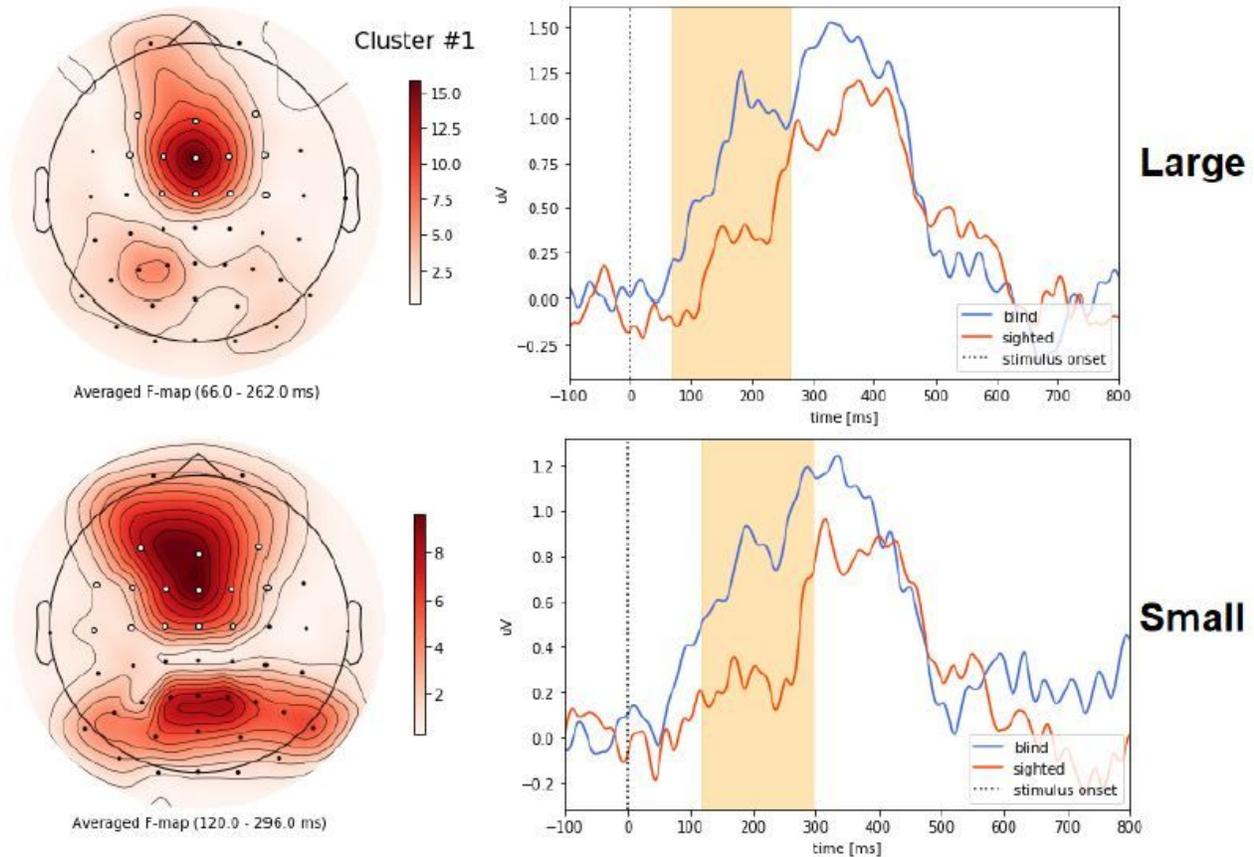


Figure 5

Significant differences between blind and sighted groups in conditions with large and small stimuli from the cluster-based permutation test. On the left is the F-score map with highlighted significant channels (white markers). On the right is the average differential waveform for the cluster. The colored area on the waveform plot corresponds to the $p < 0.05$ significance window

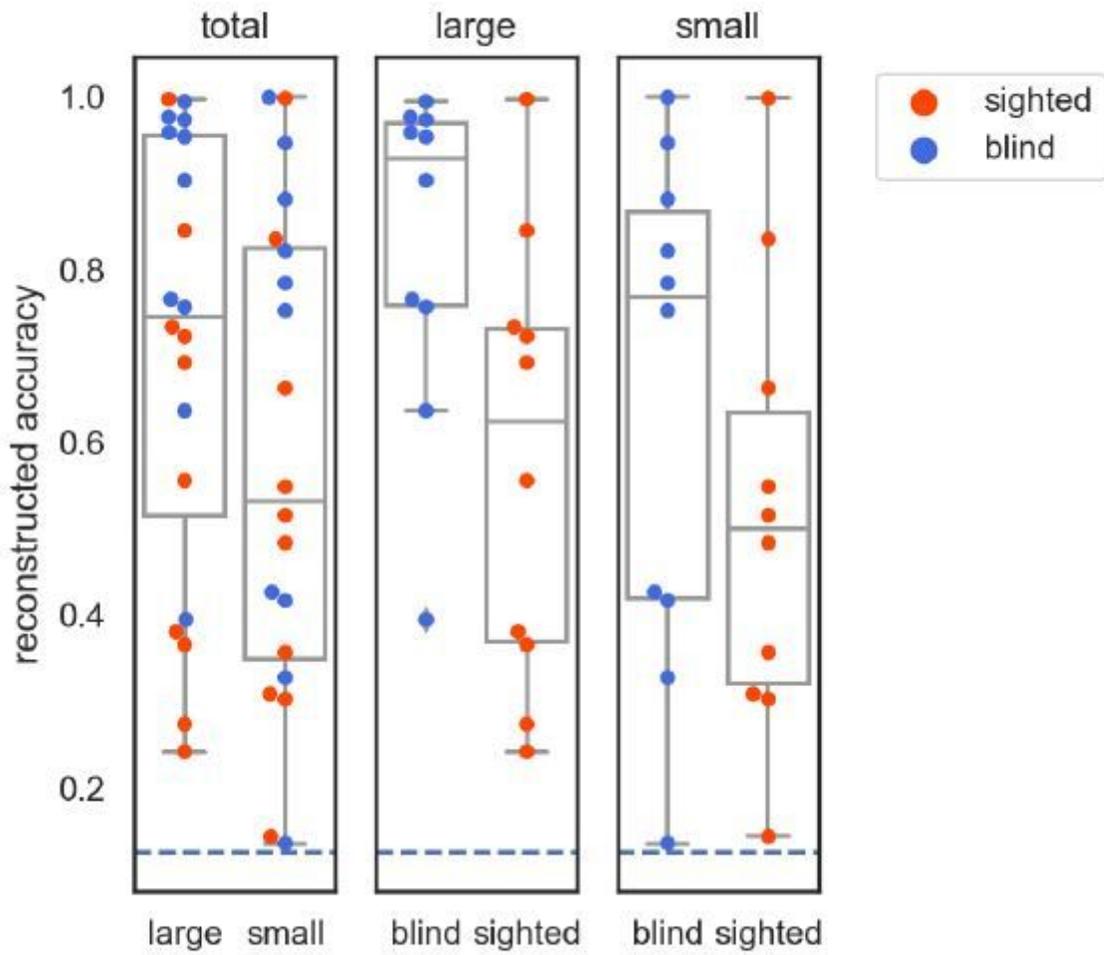


Figure 6

Reconstructed classification accuracy for all stimuli conditions (median, 25%-75% quartiles, range, data points). The dashed line represents the chance level. Diamond (⊠) marker represents an outlier.

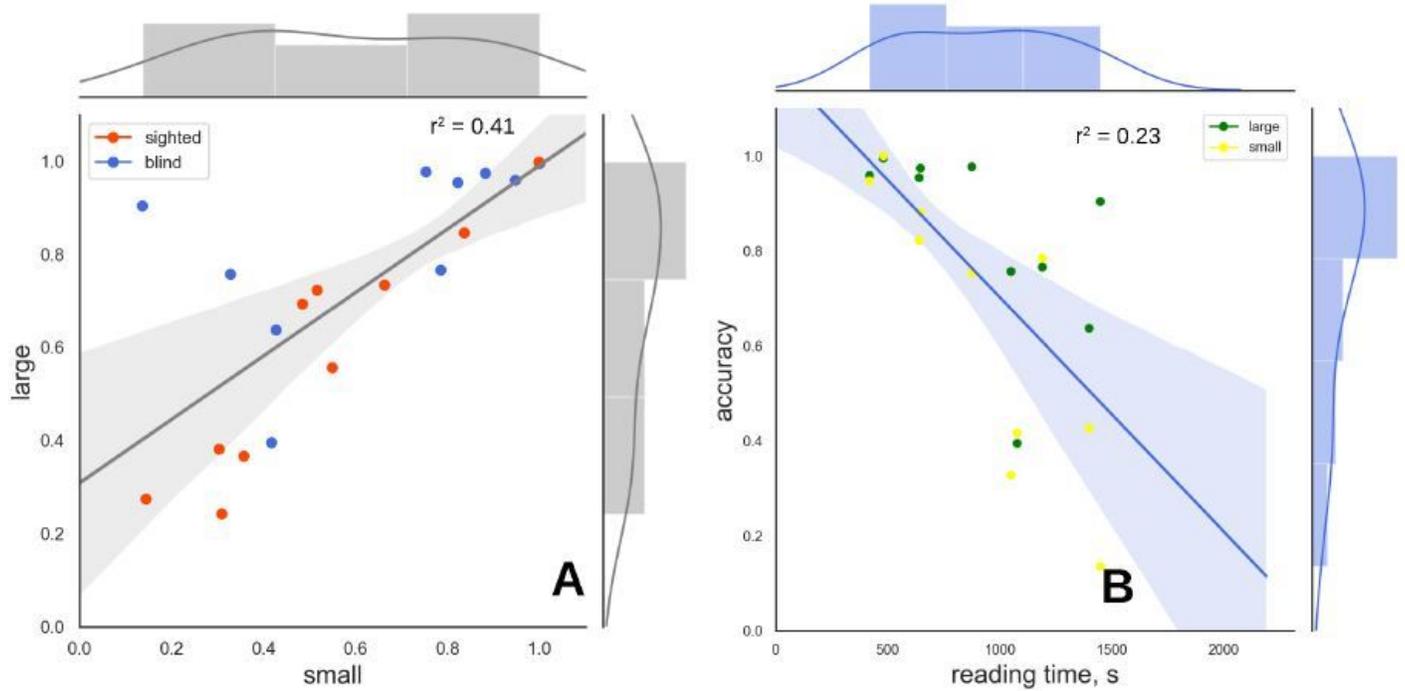


Figure 7

Correlations of classification accuracy. A - Correlation between each subject's performance in all conditions. B - Correlation between informed consent reading time and classification accuracy for blind subjects for all stimuli types.

Supplementary Files

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