Understanding human response to tactile stimuli: A Machine Learning approach

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Abstract

Whereas understanding human reaction to touch is of great interest in many medical applications, it is still a very unknown field. This research aims to clarify the nature of the relation between endogenous and exogenous attention by analysing electroencephalografic (EEG) data regarding human touch. To this end, data collected from twelve subjects under an experiment based on a variation of the Posner's cue-target paradigm has been used. After pre-processing, several multi-class classification models based on state-of-the-art machine learning algorithms have been implemented and their accuracy in detecting different experimental conditions have been evaluated. A temporal analysis has also been performed to select the most representative time points. Results showed that although the physical stimuli was identical across conditions, different types of attentional scenarios were classified above chance. Further, the hemisphere contralateral and ipsilateral to the attended side contributed differently, across time, to the accuracy of classification.

1. Introduction

In everyday life, humans can perceive the surrounding world through what is known as the five senses, responsible for connecting the environment in which we operate with our nervous system. Neural activities involved in these processes play an important role in the interpretation and responses to those stimuli. Neuropsychology science is essential to understand how our brain acts before these stimuli. Due to the growing volume and variety of available data in medicine, as well as to the cheaper and more powerful computational processing and affordable data storage, the acquisition of new knowledge on the subject is becoming increasingly easier.

Regarding the different types of stimuli and attentional scenarios to which a subject can be subjected, the brain response varies. Posner's paradigm has been widely used in neuropsychological researches to analyse these differences in brain processing at different states of attention. This paradigm is based on the presentation of a unilateral cue followed by a target at the same or opposite location. The cue can predict targets at the same (endogenous predictive task) and opposite location (endogenous counter-predictive task), or it can be a non-informative cue (exogenous task) (for further information see [1]).

Our goal in this paper is to analyze some characteristic wave sequences of the EEG tracing, called alpha-band oscillations, in this specific case caused by the attention to tactile stimuli, to detect patterns related to the type of task (endogenous predictive, endogenous counter-predictive or exogenous) being performed. Therefore, a tactile-version of the Posner's paradigm has been used. These findings can result in the determination of the neural activation most related with the different attentional scenarios, being useful in medical diagnosis or in prosthetics, such as, in the development of intelligent prostheses.

For this end, Machine Learning (ML)-based models can be used. ML is a subdiscipline of artificial intelligence (AI) aimed at building algorithms that are able to learn and/or adapt their structure based on a set of observed data (i.e., example data or past experience) [2]. ML techniques offer an approach for the analysis of high-dimensional and multimodal biomedical data.

Previous research has demonstrated that the oscillation components registered after a tactile stimulus show desynchronization and synchronization depending on the type of task. Shifting attention in space has shown to modulate alpha power in vision [3] and touch [4].

In addition, when investigating attentional shifts numerous studies have emphasized the importance of the brain lateralization function and have typically compared activations for the ipsilateral (same side) and contralateral (opposite side) hemispheres to the stimulus applied. Since brain anatomy and function differ for the left and right hemispheres, some cognitive functions tend to be dominated by one side or the other, so that it is said that the brain function is lateralized.

There is still much work to do towards the understanding of human response to tactile stimuli. Diverse statistical analyses have been carried out to try to find critical activation components, although, there has been no attempt to apply ML techniques to identify which are the most relevant time intervals in alpha oscillations waveform yet. Moreover, the importance of the brain lateralization function and whether the positivity of the ipsilateral zone or the negativity of the contralateral zone is more related to attentional tasks is still unknown.

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This paper aims at filling this research gap. The main contributions can be summarised as follows. We analyse the possibility of detecting the type of attention task by applying ML techniques on features obtained from EEG activation signals, as well as identifying the features that contribute the most to this detection. In addition, we analyse the differences regarding the laterality of the brain and finally, we analyse the agreement of these results with the raw activation signals.

2. Methods

2.1. Data collection

The data used in this study contain raw EEG wavelets from twelve participants (10 right-handed, 7 male and 5 female, aged M=25.6 years (range: 20-37 years)) who were submitted to three different types of tasks: exogenous, endogenous predictive and endogenous counter-predictive [1]. Each task involved the presentation of a tactile cue, followed by an inter-stimulus interval and the target. The participants were asked to respond as quickly as possible to the targets. EEG data were recorded using 32 electrodes arranged on the scalp of the subjects according to the 10-20 system at a sampling rate of 500 Hz. After initial pre-processing, we had available 431 endogenous-predictive, 394 endogenous counter-predictive and 258 trials for the exogenous task. For more information on the data collection experiment and preprocessing steps, see [1].

2.2. Preprocessing

First, we discarded EEGs containing artifacts and trials with behavioural errors. Moreover, only data collected by electrodes close to and around the somatosensory cortex (C3/4, P3/4 and F3/4) where kept, as these were the channels where tactile activations are found and attention effects on tactile processing are expected [1]. Then, we removed noise by smoothing the signals and we selected the time interval and frequency bands of interest. The selected time interval was 800 ms long, starting 50 ms before cue until target onset. This allowed us to get rid of the data not belonging to the cue-target interval. Since it is considered that dominant oscillations in human brain are present at the alpha band [5], we extracted these frequencies for further analysis by means of a bandpass filter. Next, we performed a downsampling of the raw EEG signals to a sampling period of 10 ms, which considerably reduced the required processing time. Finally, we computed the average of the signals by using a non-overlapping sliding time-window (TW) of 100 ms. This TW-length was selected empirically as the best value to significantly reduce the size of the data while keeping the minimum necessary detail to identify the most characteristic areas of the cue-target interval.

After the pre-processing step we had available a dataset of 864 instances (12 subjects x 3 tasks x 2 laterality conditions x attended/unattended cues x 6 electrodes) and 80 features describing the average EEG sequence values per TW, as well as the corresponding labels indicating the conditions of trial.

2.3. Data analysis

2.3.1 General activity classification by task

As previously stated, this analysis intended to find a pattern that allows grouping neural activity by tasks: exogenous, endogenous predictive and endogenous counter-predictive.

First, we split our pre-processed data into training and test sets (90% vs. 10%). Then, we built classification models for the training dataset using Random Forest (RF), Logistic Regression (LR) and Bernoulli (BNB) and Gaussian (GNB) Naïve Bayes algorithms available in *scikit-learn* toolkit for Python.

After that, we made predictions in the test dataset using our models and computed the accuracy of the models. Being our task a three-class (one class per task type) classification problem, the probability of minimum success for a random classifier would be 1/3. We are thus looking to achieve classification rates considerably above the chance value.

2.3.2 Selection of most representative time points

To estimate the relevance of each time-period to the learning stage, we computed the importance of the temporal features.

To do so, we built a classification model using RF algorithm and analysed the feature importance parameter given by the algorithm. For this process, we did not divide the cue-target interval into TWs as before, because averaging does not enable seeing features' contribution individually. Nevertheless, the consideration of individual features made data to be noisy. We smoothed the signal to capture important patterns while leaving out noise. Due to its simplicity and rapidity, the *moving average* filter has been used ($k=8$) for this purpose.

2.3.3 Consideration of the laterality of the brain

To analyse the importance of the brain laterality function and its influence in diverse sensorial modalities, the classification of the brain activations by task was performed considering the differences on signals depending on laterality. For this purpose, we separated the activations according to the laterality parameter, which caused the number of available features per trial to be reduced by half. Each trial only contained the electrodes belonging to a single hemisphere, which depended on the side where the cue appeared. We then repeated the steps 2.3.1 and 2.3.2.

2.3.4 Contrasting the results with the raw EEG signals

Finally, we compared accuracy rates to feedback the recorded raw activation patterns. These results aim to provide a clearer view of the characteristics in terms of amplitude changes in the different lobes and laterality conditions.

For this purpose, we distinguished activations by brain areas (central, frontal or parietal) and laterality, and we calculated the average value of EEG signal amplitudes for each case and per TW in the cue-target interval. This also allowed to get rid of the noise and to visualize general and repetitive patterns throughout trials.

We also compared raw activations with classification accuracy results by emphasizing in the lateralization factor, i.e. the normalized ipsilateral-minus-contralateral difference [6]. To do so, we first computed the lateralization factors per TW and then, we averaged the indexes (LI) differentiating central, parietal and frontal areas.

3. Results

Figure 1 represents the accuracy values obtained for all classifiers per TW. It shows a clear over chance accuracy, as all results overcome that of a random classifier. A bell-shaped curve can be distinguished with a peak on the interval 300 - 400 ms after cue.

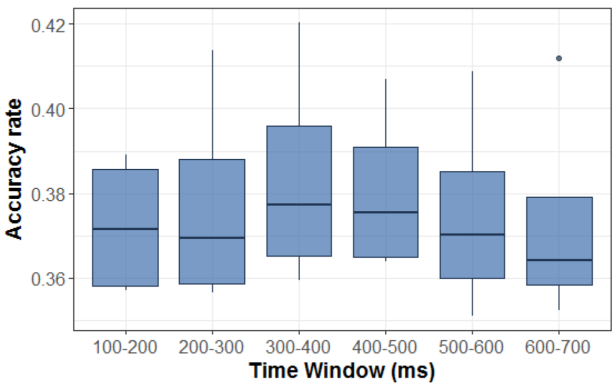

Figure 1. *Representation of accuracy values obtained for the general classification models. x axis represents the TWs in ms. y axis represents the accuracy coefficient.*

Figure 2 shows the contributions of the oscillation waves coming from different electrodes in the learning model.

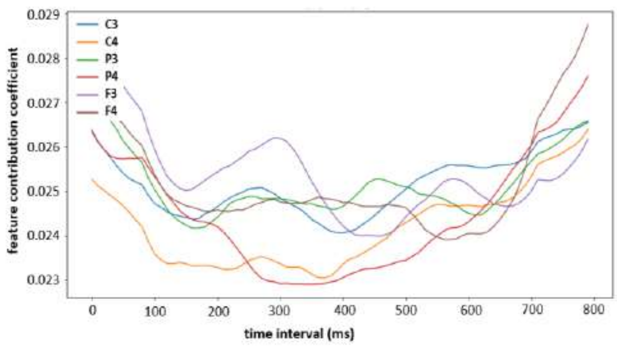

Figure 2. *Representation of the importance of each component of the activation wave measured by each electrode. x axis represents the cue-target interval in ms. y axis represents the contribution of each feature in the ML model.*

A pronounced peak around 300 ms time interval stands out for the case of the left-side frontal lobe (F3) whereas the signals recorded in the right area of that same lobe (F4) seem slightly higher than others (yet constant).

The importance to the activations registered in the left central zone (C3), follows the line of the frontal lobe, especially in the left hemisphere, although its contribution is smaller on the 300 ms time interval. However, after that instant, importance registered in the central area is greater than that in frontal zone.

Note also that central (C4) and parietal (P4) lobes of the right hemisphere do not seem to contribute much in the classification model. Nonetheless, the importance of the P4 increases slightly at the end of the 300 ms time interval.

Results in Figure 3 show that learning for the activations registered contralateral to the cue are higher than ipsilateral in a large part of the interval. However, in the last 200 ms, waves registered in ipsilateral areas get more relevance. Likewise, at the instant in which the 300 ms time interval is located, we obtained a high variability on the accuracy values for the ipsilateral activations, although the difference in the median accuracy value compared to the contralateral one is not significant.

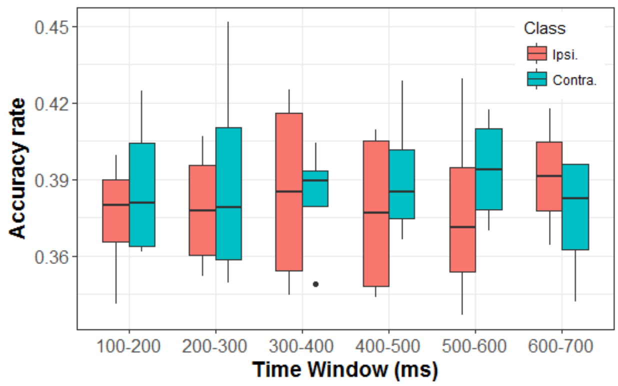

Figure 3. *Representation of the accuracy values of the classification models according to the lateralization of the brain. x axis represents the TWs in ms. y axis represents the accuracy coefficient.*

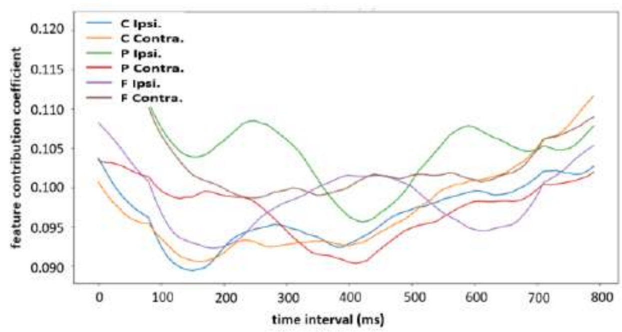

Figure 4. *Importance of activation components per electrode and laterality of the brain. x axis represents the cue-target interval in ms. y axis represents the contribution of each feature in the ML model.*

In Figure 4 a higher contralateral contribution can be distinguished, keeping it constant throughout the interval. The ipsilateral signals also show a peak around 300-350 ms after cue, posterior to the 300 ms time interval. The central zone shows the lowest values among all, although the importance of the features increases slightly in the second half of the interval, with a small peak around the 150 - 200 ms after cue. In parietal lobe the activations recorded in the area ipsilateral to the cue stand out, with a pronounced peak indicating a great contribution in the classification model around 200 ms after cue.

Figure 5 indicates that highest amplitudes are registered in the parietal zone, especially in areas ipsilateral to the stimulus, remarking that differences between central and frontal signals are quite considerable. In the case of the signals recorded in the central lobe, even though activation is in general smaller, there are differences in laterality, with considerably higher values for the ipsilateral case. The signals recorded in the frontal area do not show significant differences.

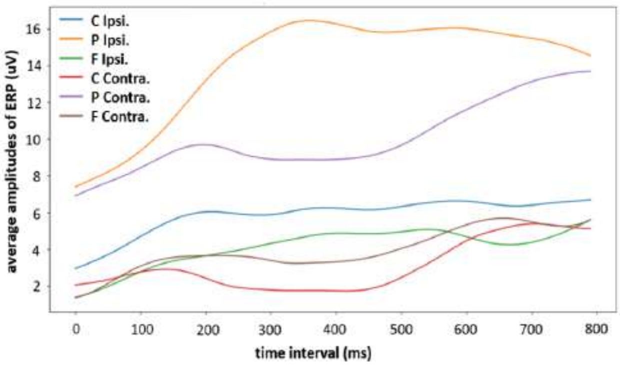

Figure 5. *Average values of the activations per cortex lobe and laterality of the brain. x axis represents the cue-target interval in ms. y axis represents mean alpha oscillations in mv.*

It should also be noted that as the time increases greater amplitudes are observed, especially where the 300 ms time interval would be located. In any case, for activations registered in contralateral areas to the stimulus an enhancement in the negativity of the waves can be observed, with a decrease in amplitude. Nevertheless, this effect is minor compared to the increase observed in ipsilateral zones.

As can be seen in Figure 6, the contralateral-minus-ipsilateral differences are larger in some time periods than in others, especially from 150 to 450 ms after cue and for signals registered in central areas.

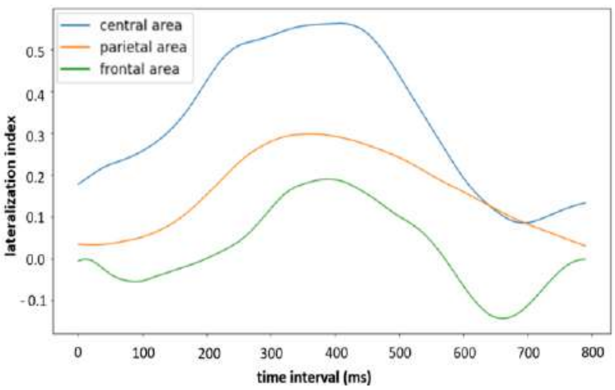

Figure 6. *Averages of the LIs of the trials regarding the cue-target interval, per somatosensory cortex area. x axis represents the cue-target interval in ms. y axis represents the LI coefficient.*

4. Discussion and conclusions

Results have shown that activation patterns are related to the conditions in which the tactile stimuli are applied. Consequently, EEG-based ML models have demonstrated to be able to distinguish between endogenous predictive, endogenous counter-predictive and exogenous tasks.

It is also significant that our simple ML models were able to predict the experimental conditions only by using data referred to the attention period, before the main stimulus occurred.

The temporal components most related to each type of attention are located around 300 ms after cue, suggesting that this time interval is the main component contributing to the prediction models. The importance of 140 ms time interval has been highlighted, after finding a great contribution in the learning process of signals registered in central contralateral areas over 150-200 ms.

Comparing the accuracy rates obtained in the classification considering the brain's laterality, we highlight the predominance of contralateral signals along almost cue-target interval. Anyway, around 300 ms time interval, the signals recorded in ipsilateral areas would also determine the differences between activations according to the type of attention. In addition, the results obtained about laterality difference, have demonstrated that the brain function is also lateralized with respect to attention in touch, where the signals registered in central lobe and around 300 ms after stimulus stand out.

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