COMPARING MACHINE LEARNING AND PREPROCESSING ALGORITHMS FOR P300 BCI SPELLER

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Abstract

This paper compares machine learning classification algorithms including logistic regression (LR), minimum distance to mean (MDM) and regularized linear discriminant (RegLDA) analysis in combination with preprocessing methods including xDAWN, Event Related Potentials (ERP) covariances and tangent space (TS), for P300 BCI speller in efforts to improve usability and make real-world applications more viable. An experiment of a checkerboard paradigm with a 8 x 9 matrix layout containing 44 Thai alphabets, 16 vowels and 7 numbers was conducted. Results show that RegLDA with xDAWN outperformed other models on P300 speller performance. This outcome helps lay the groundwork in improving the ease of use for future study on online application of P300 speller. During the experiment, the results also reveal subject-specific covariates of BCI performance, including concentration and sleepiness. The source code of this paper can be obtained from this link.

Keywords: P300 speller, BCI, EEG

1. Introduction

In the domain of Human-Computer Interface (HCI), the science and technology of Brain-Computer Interface (BCI) stands apart from most of the other HCI tools. BCI is different in that it does not require the movement or interaction of body parts (fingers, limbs, face, muscles, eyes, etc.), rather, it depends on brain activity. BCI is considered by many to be the next frontier of the evolution of man and machine as it promises new and unprecedented levels of control and interaction with computers in areas of learning, productivity, and entertainment. Most of the work to date has been focused on assistive technology in aiding disabled people who are completely paralyzed or in a locked-in state (e.g. ALS, stroke, etc.) to interface and communicate with the outside world. In the last 30 years, there has been slow and steady progress in the research and development of BCI assistive technology. Recently, conditions are ripe for major breakthroughs due to advancements in artificial intelligence, machine learning, processing power, and hardware technology. At the core of this foundation lies the P300-BCI visual speller.

The primary purpose of this work is to develop the Thai language-based P300-BCI visual speller as an assistive technology option for disabled native Thai speakers. Earlier P300 work in Thailand focused on a picture-based interface [1] rather than Thai characters due to the size and complexity of the Thai alphabet. The picture-based P300 system may not be ideal for complex writing tasks and communications. In this study, we compare different machine learning classification and preprocessing algorithms as well as subject-specific features including concentration and sleepiness on P300-BCI visual speller performance in efforts to improve usability and make real-world applications more viable.

2. Basic Concept

2.1 EEG and P300

Electroencephalography EEG was first discovered by Hans Berger in 1924 [2]. The P300-BCI visual speller concept was first introduced by Farwell and Donchin in 1988 [3]. The visual speller uses EEG signals to capture the electrical activity of the brain. The first event-related potential (ERP) was recorded by Pauline and Davis in 1935 and published the research four years later [4]. In 1964, Walter and his colleagues first reported on the cognitive ERP component, referred to as the contingent negative variation [5]. However, it is the discovery of the P3 (or P300) component in 1965 [6], which the P300-BCI visual speller approach is based on. The P300 is an event-related potential (ERP) component detected in an EEG signal approximately 300 ms after the subject is presented stimuli [7]. The P300-BCI visual speller system can identify which stimulus is task-relevant (known as the oddball event) [8]. This can be accom- plished by determining the point of the (rare) occur- rence of target stimuli, thus differentiating it from fre- quent stimuli. The P300 response is greater when the occurrence of the event is random. As early as 1971 [9], researchers began to lay the groundwork for BCI. However, it was not until 1973 when Vidal published his work titled "Toward Direct Brain-Computer Com- munications" [10] proposed the modern concept of BCI, where he suggested a man and computer interface could be used for the purpose of controlling external apparatus such as prosthetic devices or even in spaceships. Further

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work throughout the early 1980's [11] [12] [13] help lay the foundation for Farwell and Donchin in their research of the P300 component of the event-related brain potential (ERP) that led to the development of the BCI Visual Speller using the P300 control signal [4].

2.2 Matrix Paradigm

The first speller that was developed by Farwell and Donchin in 1988 [4] presented the subject with a 6x6 matrix containing alpha-numeric characters utilizing the English alphabet. The matrix contained 6 rows and 6 columns that randomly flashed with a predetermined duration and interval. The subjects were asked to focus on a specific target character and count each time that it flashed. It was expected that the flashes of the target character would evoke a P300 potential as the subject focused on it. The P300-BCI Speller system would learn to predict the character the subject focused on based on identifying these evoked responses via the P300 ERP signal.

P300-BCI spellers that utilize a row and column matrix paradigm (RCP) present inherent challenges and limitations in its design and performance. The size, layout, color, contrast, background, and brightness of the matrix, and the characters affect performance and usability. A matrix design may affect a subject's perceptual performance and accuracy. For example, when characters are crammed together tightly, subjects have difficulty in accurately targeting them because of poor spatial distribution [14] [15] [15], this is known as the *crowding effect* [16]. Besides, when characters surrounding the target character flashes, this may cause false triggers known as *adjacency errors* [17]. Subjects may also experience fatigue during longer trials due to larger matrix size and higher repetitions. Subjects may experience repetition blindness due to attentional blinks, or identical targets are triggered within the series of fast row/column flashes, causing the second target to be missed [18] [19] . To avoid the adjacency-distraction and double-flash errors to which the RCP is prone to, an alternative, the checkerboard paradigm, (CBP) was introduced by [20]. Another paradigm called region-based paradigm was also proposed by [21] where a two-level speller flashes in regions instead of rows and columns. However, in this work we focus on comparing the machine learning and preprocessing techniques, thus we implemented the P300 with CBP for simplicity.

3. Preprocessing

Though the raw EEGs contain the desired P300 evoked potentials, it also contains the ongoing activities (e.g. brain activities, muscular, ocular, pulse artifacts). Subsequently, this low signal to noise ratio (SNR) makes the classification task difficult. Several methods such as xDAWN [22], ERP covariances [23] and Tangent Space [24] have been explored. xDAWN is a simple and unsupervised estimation which projects the raw recorded EEGs on the estimated evoked subspace and as a result, the ERPs are enhanced [22]. xDAWN provides a classification accuracy of 80% which is higher than that of ICA which could achieve 71% on only five symbol repetitions [22]. On the other hand ERP covariances [23] work on the covariance matrix estimation which time structure of the signals is normally neglected. It instead builds covariance matrices in which the spatial and temporal structural information are both taken into account allowing the purposeful application of Riemannian geometry for ERP data. Lastly, as for the tangent space algorithm, the vectorized covariance matrices are considered as Euclidean objects and then mapped onto the Riemannian tangent space. To decrease dimensionality, a variable selection procedure is applied and lastly a classification by LDA is performed [24]. As a result, an increase of the mean classification accuracy from 65.1% to 70.2% of motor imagery based classification was observed [24].

3.1 Classification Models

Determining the presence or absence of a P300 evoked potential from EEG features can be considered a binary classification problem. [25] employed logistic regression (LR) which is suitable for a binary classification task in order to explore important fea- tures for P300 detection improvement. [26] employed LDA which is based on a probabilistic regression net- work. [27] also reported that LDA, a linear classifier, serves as a good baseline performer. The minimum distance to mean (MDM) is a classification algorithm which is based on the comparison of distances, es- pecially with Riemannian distance which has shown great performance [28]. This is done by training a classifier consisting in the estimation of a mean co- variance matrix for each class and its Riemannian geometric mean which represents the expected dis- tribution. Therefore, an unknown class y is simply achieved by looking at the minimum distance to each class's Riemannian geometric mean.

4. Methodology

4.1 Subject

A healthy male adult of age 26 with normal vision participated in this study. The subject was instructed to have at least 7 hours of sleep before the experiment and to not consume caffeine on the day of the experiment. The participant had experience with EEG recording and P300 speller.

4.2 Data Acquisition and Apparatus

For EEG acquisition, EEG was recorded using a Electro-Cap International Inc. cap embedded with 16 electrodes with the sampling rate of 125 Hz distributed over the entire scalp. Only 8 channels of electrodes (Fz, F3, C4, Cz, Pz, P3, O2 and O1) were observed and referenced to the Cz position (See Fig. 1). All signal channels are connected and obtained from a Cyton board designed by OpenBCI. The pin wiring system was modified to connect using the connector. The cap is wired to 8 male pins connector, and the Cyton Board is wired to the 8 female pins connector. Bluetooth was used with the board receiver. For software, OpenBCI GUI + Hub was used to ensure that all electrodes are working correctly after the participant put on the cap. Salt-based electro-gel was used as a conductive medium and a LCD monitor (screen size: 24 inch, resolution: 1920 x 1080, refresh rate: 60 Hz) was used during the experiment.

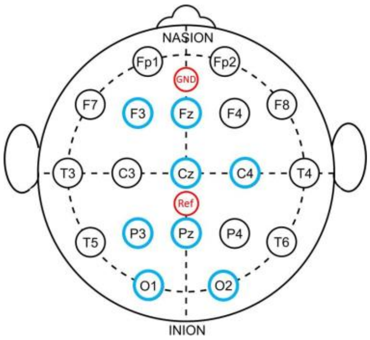

Figure 1. Electrode Positions

4.3 Task, procedure and design

We have adapted the P300 speller layout from [20] called the checkerboard paradigm, where 44 Thai alphabets, 16 vowels, 4 tone marks and 7 numbers are placed in a 8 x 9 matrix (See Fig. 2). The matrix is virtually superimposed on a checkerboard pattern, which the subjects never see. Before each sequence of flashes, the items in white cells randomly fill a virtual 6 x 6 white matrix and the items in the black cells randomly fill a virtual 6 x 6 black matrix (See Fig. 3). During one sequence, the 6 virtual rows in the white matrix flash in order from top to bottom followed by the 6 rows in the black matrix (See Fig. 4). Then the six virtual columns in the white matrix flashes in order from left to right followed by the six columns in the black matrix, vice versa.

This virtual checkerboard layout tackles 2 common errors in P300 spellers, the adjacency error and the double-flash error. The adjacency errors arise when one of the four items adjacent to the target flashes at the same time with the target and distract the participant's attention, thereby producing P300 responses that cause the item to be selected unintentionally. On the other hand, double-flash errors occur when the target item flashes twice in immediate succession, causing reduction of P300 amplitude or changing morphology. These two types of errors are eliminated by the checkerboard paradigm. With the checkerboard layout, adjacent items (white and black) cannot be in the same flash group and the flash sequence of the white and black matrix constraints that there are at minimum of 6 and maximum of 18 flashes between two flashes of the same item.

Each flash group flashes for 62 ms, followed by a 62 ms inter-stimulus interval (ISI). Thus, a group flashes every 124 ms (i.e., 8 flashes/s). Twenty four flashes (from 12 columns and 12 rows) make up one complete sequence. For each item selection, five complete sequences or five repetitions occur (i.e., any target item flashes 10 times). A 3500 ms break is added between items.

Per one letter we obtain 110 non-target events and 10 target events. Thus, from one six-word spelling session, a total of 3960 non-target events and 360 target events are obtained.

Figure 2. P300 Visual Speller Display Layout

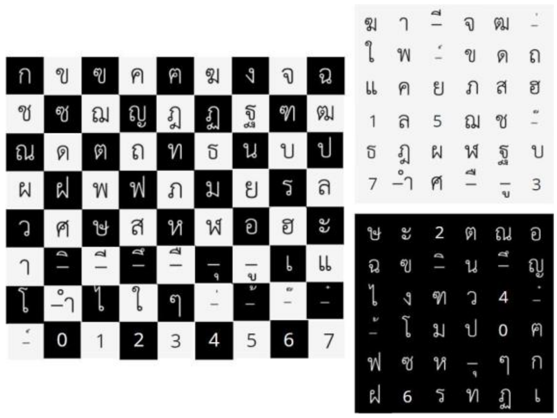

Figure 3. Checkerboard paradigm: the items in white cells randomly fill a virtual 6 x 6 white matrix and the items in the black cells randomly fill a virtual 6 x 6 black matrix

Six training sessions were performed on the first day of the experiment, followed by 3, 2 and 2 online sessions on the second, third and fourth day respectively. The training sessions served to gather data and used to derive the classification models for the online runs. No feedback was shown in the training session. The seven online sessions were used to calculate the accuracy (average success rate). Feedback of each trial was shown to the participant in the online sessions by showing their classification result (the output letter) which takes an extra time of 1000 ms between each trial. Each session consists of six trials (i.e., six target letters). In each trial, the subject was instructed to focus on the target character and count the times the target character flashed to ensure that concentration was maintained. Every target character of a trial was randomized for all training sessions and online sessions. The target characters' background is highlighted for 3500 ms during the break between trials to indicate the target. Then the letters flashed according to the virtual checkerboard layout until all six trials finished.

Figure 4. Example of first flash group of a flash sequence: the flashing characters are from the first row of the virtual white matrix

4.4 Signal Processing

The goal of the preprocessing stage is to increase the signal-to-noise ratio.

Power-line noise is a noise created by the electrical network. In Thailand, it is composed of sharp peaks at 50Hz. Some peaks may also be present at the harmonic frequencies, i.e. the integer multiples of the power-line frequency. Thus, we used a notch filter to remove the frequency at 50 Hz as well as its harmonics, i.e., 100Hz, 150Hz, etc. Since our signal is 125Hz (250Hz/2 according to [29]), we shall run the harmonics until 125 Hz. Next, we filtered the signals using a Butterworth bandpass filter with cut-off frequencies at 1 Hz and 20 Hz to capture the relevant frequencies of P300. As the name P300 suggests, the ERP happens 300ms after the event has occurred. Therefore, to increase SNR, the EEG signals are epoched from 200 ms to 500 ms.

Lastly, we explored three different preprocessing techniques adopted from the pyriemann library: xDAWN, ERP covariances and tangent space. xDAWN is a spatial filtering method designed to improve the signal to signal+noise ratio (SSNR) of the ERP responses. It enhances the target response with respect to the non-target response [22]. Number of components for xDAWN was set to 3. ERP covariances estimate a special form covariance matrix for ERP. It allows us to take into account the spatial structure of the signal [23]. We used oracle approximating shrunk covariance matrix in both xDAWN and ERP as it is a regularized covariance matrix estimator. Tangent space bridges euclidean space and Riemannian manifolds. It projects covariance matrices belonging to the Riemann manifold into Euclidean space vectors. By using this mapping, one can use classical and efficient classifiers such as logistic regression on covariance matrices directly, instead of using MDM.

4.5 Classification

From previous steps, we achieved a total of 4320 samples which consisted of 3960 non-target and 360 target samples. Each sample consists of 8 sequences from each electrode and each sequence is of length 76. For each classification model we performed 15-fold cross validation with Stratified KFold (random state was set to 42).

P300 Speller is based on a binary classification problem where the ERP of the target and non-target stimuli must be identified. In order to find out which specific character the participant is looking at, we employ 3 different binary classification methods from sklearn namely LR, MDM, and RegLDA analysis.

Logistic regression is a supervised learning classification algorithm used to predict the probability of a target variable. In our case, the two classes are target/non-target. The configurations of this model were set to penalty=l1, solver=liblinear and multi class=auto. MDM classifier is a classification model that assigns to observations the label of the class of training samples whose mean (centroid) is closest to the observation. This classifier works by calculating covariance mean matrices for each class in training data as a representative and assigns the label to test data by calculating their distances from mean covariance matrices of classes. We used the sklearn's default configurations for MDM. RegLDA estimates the probability that a new set of inputs belongs to every class and outputs the class with the highest probability. The configurations of this LDA were set to shrinkage=auto and solver=eigen.

The models' performance were measured by sklearn's classification report and the cross validation score were reported in terms of AUC ROC score.

4. Results

We report the result of waveform analysis, models' accuracy, and information transfer rate.

4.1 Waveform Analysis

To check the P300 occurrences, the average waveforms at electrodes Fz, F3, C4, Cz, Pz, P3, O2 and O1 were analyzed. Fig. 5 presents plots of average EEG signals of non-target and target with topographies. The target condition shows a positive voltage component of P300 response at approximately 250-275 ms after the stimulus onset, while this was not present in the non-target condition. Note that the P300 could normally occur anywhere between 250-400 ms post-stimulus onset [30].

As shown in Fig. 6, when topographical subplots of average target (orange) and non-target (blue) ERPs are plotted, P300 peaks of target ERPs can be seen clearly at occipital (O1, O2) and parietal (P3) regions but not as prominent on the midline electrodes (Cz, Fz).

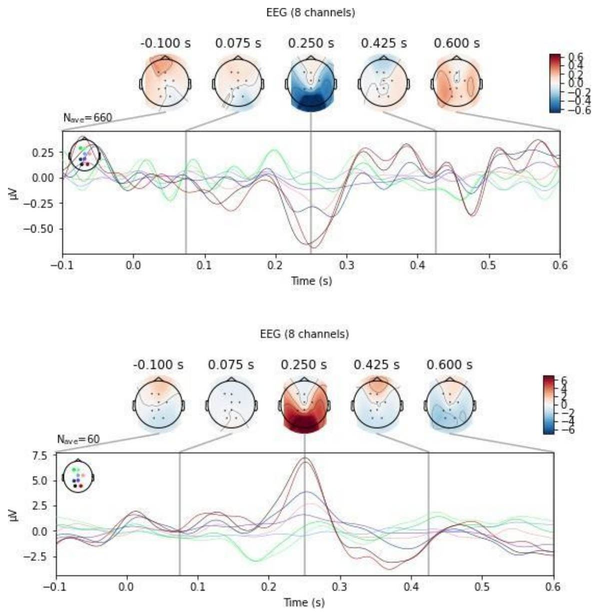

Figure 5. Average waveforms of each electrode of non-target (top) and target (bottom) from the first online session with topographies

4.2 Performance Metrics

Next, we trained four classification models with four different combinations of preprocessing techniques and classification algorithms on the EEG signals acquired from the training sessions. Performance of the models are reported in terms of precision, recall, f1-score, accuracy (See Table 1), area under the receiver operating characteristic curve (AUC ROC) (See Fig.7).

ERP+TS+LR and xDAWN+RegLDA achieved similar performance and outperformed xDAWN+MDM and ERP+MDM for all metrics. This suggested that the MDM model is prone to produce more false negative than false positive predictions which was as expected as there are far more non-target samples than target samples in the training dataset. The reason is likely due to MDM's inability to model the non-stationary nature of EEG signals. Hence, LR and RegLDA can better model EEG signals given their statistical properties.

Table 1: Precision, recall, f1-score and accuracy of each model

Model	Precision	Recall	f1-score	Accuracy
ERP+TS+LR	0.93	0.94	0.93	0.94
ERP+MDM	0.92	0.80	0.84	0.80
xDAWN+RegLDA	0.93	0.93	0.93	0.93
xDAWN+MDM	0.92	0.82	0.82	0.82

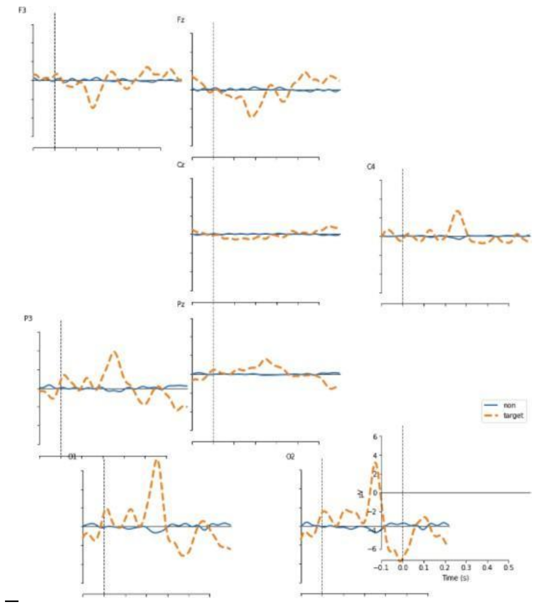

Figure 6. Topographical subplots of average target ERP (orange) and non-target ERP (blue) from the first online session

4.3 Information Transfer Rate

Since the performance of ERP+TS+LR and xDAWN +RegLDA were similar in precision, recall, f1-score as well as accuracy and due to the imbalance of our data, we selected the best model according to AUC ROC score which was xDAWN + RegLDA. Therefore we used this in our information transfer rate analysis.

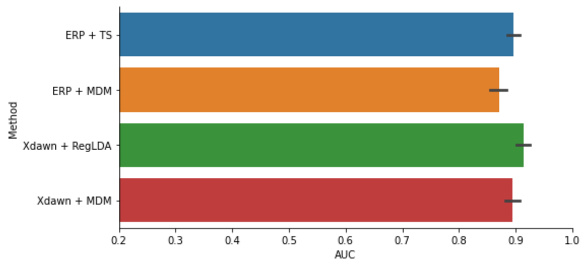

Figure 7. AUC ROC of each model from a 15-fold cross validation on data of all 6 offline sessions.

Blue is the result of ERP covariance and tangent space as signal processing and LR as classification model. Orange is the result of ERP covariance as signal processing and MDM as classification model, green is with xDAWN as signal processing and RegLDA as classification model and lastly, red is with xDAWN as signal processing and MDM as classification model.

Information Transfer Rate (ITR) is the standard method for measuring the performance of BCI. It is the amount of information transferred per unit time (bits/min) calculated with the following formula [31], where B is information transferred in bits per trial, N is the number of target classes, and P is the rate of correctly classified commands to the total number of commands :

$$B = log_2 N + P \cdot log_2 P + (I - P) \cdot log_2(\frac{I-P}{N-I}) \text{ (bit per trial)} \quad (1)$$

To obtain the ITR in bits/min, B is multiplied by Q which is the average classification time in minutes where S is the number of trials per minute and T is the total time.

$$Q = \frac{S}{T} \quad \text{(trial per min)} \quad (2)$$

$$ITR = B \cdot Q \text{ (bit per min)} \quad (3)$$

In our experiment, N is 72 (from the 8 x 9 matrix). We conducted a total of seven online sessions with 6 trials each. The model was able to classify 32 out of 42 trials correctly, thus P is 0.7619. According to the equations, B is 3.913 bit/trial and Q is 2.608 trials/min are obtained. Finally, an ITR of 10.205 bit/min is achieved.

We also tested the speller on 2 other subjects. We conducted 6 training sessions on both subjects to get the training data. On the first participant, we conducted 2 online sessions (one with 6 letters and one with 4 letters) and achieved an accuracy of 0.70 (7 correctly classified out of 10). For the second participant, 2 online sessions were conducted and an accuracy of 0.50 (6 correctly classified out of 12) was achieved.

5. Discussion

Our results were consistent with past work, showing that P300 peaks at around 250-400 ms after the stimuli onset. Moreover, P300 is most prominent in the occipital region which is the region responsible for human vision.

As we have found, the best performing model was xDAWN+RegLDA which achieved cross-validation accuracy of 93% in training sessions and 76% in online sessions. The difference of validation accuracy between training sessions and online sessions is likely due to random factors such as user's concentration, different days of sessions, and slightly different cap positions that may not be fully captured in the training sessions.

Indeed, during our research, we observe that concentration of the participant, eye fatigue, and sleepiness greatly affect the performance of our P300 speller and thus leads to different performances across participants. Therefore, it is advised that participants should have a good sleep and meditate if possible.

For classification models, a particular worst performer has been consistent whenever MDM was used. One possible explanation is that mean distances may not be the best central tendency metric for estimating the distributions of P300 or of EEG in general. On the other hand, RegLDA and LR were able to effectively classify the P300 signal after certain preprocessing techniques. Since RegLDA and LR were two relatively simple classifiers, it may be safe to assume that once P300 signals were effectively preprocessed, any classifier algorithm should work relatively well, implying the importance of preprocessing algorithms. Although we have successfully implemented the first Thai language-based BCI speller, the speller only achieved an ITR of 10.205 bit/min or around 1.25 words/min. For future work, it may be wise to integrate steady state visually evoked potentials (SSVEP) to our current P300 system to make it a hybrid SSVEP-P300 BCI speller which will allow less training time and higher ITR.

6. Conclusion

This study contributes to the development of the first Thai language-based BCI speller that fully relies on only brain signals without any eye-tracking or other input modalities. We have compared four different models which combine different machine learning algorithms and preprocessing techniques. We found that ERP and xDAWN were effective preprocessing techniques while both LDA and LR classification models perform relatively well. This work provides a practical and theoretical foundation for the development of Thai language-based BCI speller.

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References

[1] S. Jirayucharoensak et al. "Design and Evaluation of a Picture-Based P300 AAC System". In: *Proceedings of the 5th International Conference on Rehabilitation Engineering % Assistive Technology*. i-CREATe '11. Midview City, SGP: Singapore Therapeutic, Assistive % Rehabilitative Technologies (START) Centre, 2011.

[2] Hans Berger. "Uber das elektroenkephalogramm des menschen". In: *Archiv fu¨r psychiatrie und nervenkrankheiten* 87.1 (1929), pp. 527–570.

[3] Lawrence Ashley Farwell and Emanuel Donchin. "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials". In: *Electroencephalography and clinical Neurophysiology* 70.6 (1988), pp. 510–523.

[4] Terence W Picton. "Hallowell Davis and evoked potential audiometry". In: *The Journal of the Acoustical Society of America* 95.5 (1994), pp. 2866–2867.

[5] W Walter et al. "Contingent negative variation: an electric sign of sensori-motor association and expectancy in the human brain". In: *nature* 203.4943 (1964), pp. 380–384.

[6] Samuel Sutton et al. "Evoked-potential correlates of stimulus uncertainty". In: *Science* 150.3700 (1965), pp. 1187–1188.

[7] John Polich. "On the relationship between EEG and P300: individual differences, aging, and ultradian rhythms". In: *International journal of psychophysiology* 26.1-3 (1997), pp. 299–317.

[8] Emanuel Donchin. "Surprise!..surprise?" In: *Psychophysiology* 18.5 (1981), pp. 493–513.

[9] Eberhard E Fetz and Dom V Finocchio. "Operant conditioning of specific patterns of neural and muscular activity". In: *Science* 174.4007 (1971), pp. 431–435.

[10] Jacques J Vidal. "Toward direct brain-computer communication". In: *Annual review of Biophysics and Bioengineering* 2.1 (1973), pp. 157–180.

[11] Theodore R Bashore and Maurits W Van der Molen. "Discovery of the P300: a tribute". In: *Biological psychology* 32.2-3 (1991), pp. 155–171.

[12] Steven A Hillyard and Marta Kutas. "Electrophysiology of cognitive processing". In: *Annual review of psychology* 34.1 (1983), pp. 33–61.

[13] E Donchin, GA Miller, and LA Farwell. "The endogenous components of the event-related potential—A diagnostic tool?" In: *Progress in brain research*. Vol. 70. Elsevier, 1986, pp. 87–102.

[14] Chengzhi Feng, Yi Jiang, and Sheng He. "Horizontal and vertical asymmetry in visual spatial crowding effects". In: *Journal of Vision* 7.2 (2007), pp. 13–13.

[15] Alexander Toet and Dennis M Levi. "The two-dimensional shape of spatial interaction zones in the parafovea". In: *Vision research* 32.7 (1992), pp. 1349–1357.

[16] Hans Strasburger. "Unfocussed spatial attention underlies the crowding effect in indirect form v sion". In: *Journal of vision* 5.11 (2005), pp. 8–8.

[17] Reza Fazel-Rezai. "Human error in P300 speller paradigm for brain-computer interface". In: *2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2007, pp. 2516–2519.

[18] Nancy G Kanwisher. "Repetition blindness: Type recognition without token individuation". In: *Cognition* 27.2 (1987), pp. 117–143.

[19] Kimron L Shapiro, Jane E Raymond, and Karen M Arnell. "Attention to visual pattern information produces the attentional blink in rapid serial visual presentation." In: *Journal of Experimental psychology: Human perception and performance* 20.2 (1994), p. 357.

[20] George Townsend et al. "A novel P300-based brain–computer interface stimulus presentation paradigm: moving beyond rows and columns". In: *Clinical neurophysiology* 121.7 (2010), pp. 1109–1120.

[21] Reza Fazel-Rezai and Kamyar Abhari. "A region-based P300 speller for brain-computer interface". In: Canadian Journal of Electrical and Computer Engineering 34.3 (2009), pp. 81–85.

[22] Bertrand Rivet et al. "xDAWN algorithm to enhance evoked potentials: application to brain– computer interface". In: *IEEE Transactions on Biomedical Engineering* 56.8 (2009), pp. 2035–2043.

[23] Alexandre Barachant and Marco Congedo. "A plug&play P300 BCI using information geometry". In: arXiv preprint arXiv:1409.0107 (2014).

[24] Alexandre Barachant et al. "Multiclass brain–computer interface classification by Riemannian geometry". In: IEEE Transactions on Biomedical Engineering 59.4 (2011), pp. 920–928.

[25] Sadraque S Viana, Danilo M Batista, and Danilo B Melges. "Logistic regression models: Feature selection for P300 detection improvement". In: *XXIV Congresso Brasileiro de Engenharia Biomédica-CBEB, Belo Horizonte*. 2014.

[26] Ulrich Hoffmann et al. "An efficient P300-based brain–computer interface for disabled subjects". In: *Journal of Neuroscience methods* 167.1 (2008), pp. 115–125.

[27] Dean J Krusienski et al. "A comparison of classification techniques for the P300 Speller". In: *Journal of neural engineering* 3.4 (2006), p. 299.

[28] Alexandre Barachant et al. "A brain-switch using riemannian geometry". In: BCI 2011-5th International Brain-Computer Interface Conference. 2011, pp. 64–67.

[29] Claude Elwood Shannon. "Communication in the presence of noise". In: Proceedings of the IRE 37.1 (1949), pp. 10–21.

[30] James Wilbur Hall. Handbook of auditory evoked responses. Allyn & Bacon, 1992.

[31] Jonathan R Wolpaw et al. "Brain–computer interfaces for communication and control". In: Clinical neurophysiology 113.6 (2002), pp. 767–791.

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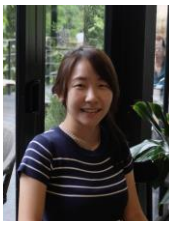

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