Towards an Efficient and Convenient Brain Computer Interface

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Abstract

Highly sensitive low noise electrodes, capability of fast processing of multivariate signals, low cost of hardware and wireless communication have widen the possibilities of the use of electroencephalogram (EEG) data for various applications. These applications are not only restricted to medical investigations (like epileptic seizures, monitoring anesthesia or brain function etc.), but also for well-being of disabled patients, as well as for entertainments like playing games. Our focus in this study is BCI applications based on identification of Event Related Potential (ERP) P300. One such application is BCI speller, which is used in our experiments. BCI spellers, on the market, use 8 probes and take 72 seconds to collect data to reliably spell a single character. The motivation of this work is to reduce the number of probes and the time needed to spell a letter. A commercial product should reliably work for every user (customer). Such a large number of probes and long time to spell a letter are necessary to ensure correct recognition. We have shown that if we identify the position of the probes appropriately for an individual, as few as two probes could give even better results. All experiments are conducted at our in-house facility, where most of the subjects undergone no prior training.

Presence of electrical waves from monkey's brian was first reported by a British doctor, Richard Caton, in as early as 1875. Hans Berger, a German psychiatrist, first recorded human brain waves aka ElectroEncephaloGram (EEG), in 1924. After a short pause during second war, research with EEG signals received more and more attention, as the sensitivities of electrical probes improved to detect feeble signals, and the cost of computation for analysing multivariate signals from several probes were decreasing. EEG signals are very weak, of the order of a few microvolts when measured using probes fitted on the scalp. It is necessary that artifacts from biological activities like eye-blinks, eye-movement, ECG, EMG, as well as external environmental artifacts are to be mitigated. In addition, EEG's spatial resolution is poor. In other words, mapping EEG signal to activity at a particular region of the brain is difficult. Still, because of high temporal resolution, and low cost, EEG is finding many applications (Okuma 1999).

Though electroencephalogram (EEG) signals are weak, of the order of a few microvolts, with the advent of highly sensitive probes, amplifiers and noise reduction techniques, those EEG signals could be a rich source of information about what is happening inside the brain. What we think, intend to do, our emotions, all are reflected as electrical signals in brain neurons. By analyzing EEG signals, we could not only design medical applications but also can use them as a means of communication and to play games. In diseases like amyotrophic lateral sclerosis, or ALS, the nerve cells in the brain and the spinal cord die. Though the brain remains active, the patients become disabled and cease to speak, or communicate using gesture. Brain Computer Interface (BCI) Speller is a means by which these patients could communicate. Other common BCI applications are moving a wheelchair in the intended direction, or playing computer games. In many such applications a special EEG signal, P300, is used. The motivation of this work is to improve the efficiency of identifying P300.

Event Related Potential P300

A class of EEG signals is called Event Related Potentials (ERPs), which are evoked as a result of some stimulus or event, like an audio or a visual or a somatosensory stimuli (Luck 2005). Of all the EEG signals, ERP P300 is the strongest, and therefore easy to identify. Naturally, it is used in many Brain Machine Interface applications.

P300 is a special kind of ERP. When we expectantly wait for something rewarding or alarming to happen, which would happen with low frequency at random intervals, our brain generates a strong positive signal when it actually takes place. It is called Event Related Potential (ERP) P300. ERPs are named according to whether the potential is Positive (P) or Negative (N), and the time delay from stimulus to the occurance of the potential. For P300, P stands for positive, and 300 is because the signal appears approximately 300 milliseconds after the occurrence of the stimuli. P300 is generated after the external stimulus (for example a visual image) is perceived in the brain, and with respect to our previous experience, knowledge or training, is concluded as rewarding or alarming. The cognitive process in the brain's pareto region takes time and causes the delay. This sudden feeling of euphoria/danger synchronously activate a large number of neurons, which creates a strong positive signal over a wide region on the surface of the brain. It can easily be detected by electrical probes attached to the scalp. This principle of

interface, by identifying P300, is used to design many BCI applications.

Motivation of this Work

Helping communication for ALS or spinal cord injured patients by using BCI is one important area of research and development. Its working principle is simple. The subject chooses letters in sequence, one at a time, from the word he intends to spell. Different characters flash on the display at random intervals. When the chosen letter flashes, the subject's brain is stimulated to generate ERP300 signal, because identifying it is like a reward to her. The signal is strong as it happens occasionally, at random intervals, and the subject has to concentrate so that he does not miss it. Due to external noise, spurious noise from brain and other instabilities, due to individual's variations, for identifying ERP300 signal multiple probes are used at different positions on the scalp. The robustness of the system is improved when multivariate signals are analyzed together. In addition, for a sigle letter, the experiment is repeated several times to reduce the probability of misclassification. Commercially available BCI speller (EGI 2010) used 8 probes, and takes 72 seconds to read a single character. The motivation of this work is to reduce the number of probes and the time to spell a letter.

Organization of the Manuscript

The paper is organized as follows. Following introduction, in section 2, we will explain the working principle of BCI speller. In section 3, we describe the experimental set-up and its details. In section 4, our approach to reduce the number of probes is explained. Section 5 includes experimental results and comparisons with previous works. Finally, we conclude the paper in section 6, indicating future works.

Working Principle of BCI Speller

In this work we will focus on BCI speller, though the idea of efficient identification of P300 could be extended to other applications. The basic principle of the working of BCI speller is as follows. In P300 BCI Speller, the display consists of a matrix of English alphabets and numerals. These 26 characters and 10 numerals are arranged in a 6×6 matrix form, as shown in Fig. 1. As the spelling task begins, a particular row or column flash at a time. To communicate a single character or numeral, all the six rows and six columns flash for 10 times. The flashing occurs with random uniform probability distribution. The duration of the flash is 600 ms. Thus, the time required to communicate a single target character/numeral is $(6 + 6) \times 10 \times 600ms. = 72$ Sec. Every time the character to be communicated is included in the row or column which is flashed, the subject is to count up. The subject needs to concentrate, so as not to miss the flash of the intended character, which happens at irregular intervals. The success of the detection creates a strong ERP P300, or in short P300, which is detected by the probes attached on the scalp. To read one character, we get 20 signals with ERP and 100 without. Once those 20 flashing rows/columns with P300 are identified, the intended character is known, as the one at the cross point of the row and the column. We need

Figure 1: P300 BCI Speller Display

to classify those 120 signals into two groups, with P300 and without P300. Subjects concentrate, not to miss a target flash for which the probability is low $(20/120 = 1/6)$. If the probability is made lower, P300 signal will be stronger, but at the cost of longer time needed to communicate a character. The strongest P300 signal does appear near central and parietal region of the brain. But the location for strongest signals vary from person to person. Eight probes, spread over central and pareto region of the brain, are used for commercial products, This is to ensure that the machine works for everyone.

In this work, we will show that if we design BCI speller for individual use, we can reduce the number of probes. An ALS patient, who needs such communication tool, it is worth to find proper probe location/s. We can then reduce the cost of the equipment, do the processing efficiently, as well as increase the spelling accuracy.

In our experiment, we collected EEG signals from many probes, group them into clusters, and select one representative probe from each cluster. A fewer selected probes, for all subjects, gave better recognition results. The results are stable over a time, i.e. the probe locations do not change when experiments performed are stretched over one year. In our previous work, we arbitrarily fixed the number of probes to 4 (Yokoha, Chakraborty, and Kikuchi 2014). In this report, we will show that further reduction is possible by running multi-objective combinatorial optimization algorithm to select relevant probes. In fact, better classification results were obtained with even fewer than four probes. The results are compared with our previous work (Yokoha, Chakraborty, and Kikuchi 2014) and another work (Hoffmann and et.al. 2008).

Experimental Set-up

In conventional BCI speller (EGI 2010), 8 probes on the central and pareto region of the brain are used. Their positions are Fz, Cz, Pz, Oz, $P7$, $P3$, $P4$, $P8$, as shown in Fig. 2. Here, F, C, P, O, z stand for Frontal, Central, Parietal, Occipital, and z for the central line dividing the head into left hemisphere and right hemisphere. Left hemisphere probes are numbered odd, and the right are numbered even. $P7$, $P3$ are on the left hemisphere and $P4$, $P8$ are on the right hemisphere. Our motivation is to find the location of the strongest

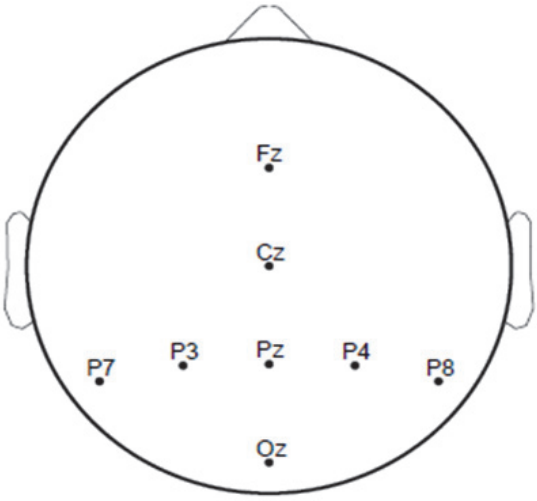

Figure 2: Position of 8 probes in BCI Speller

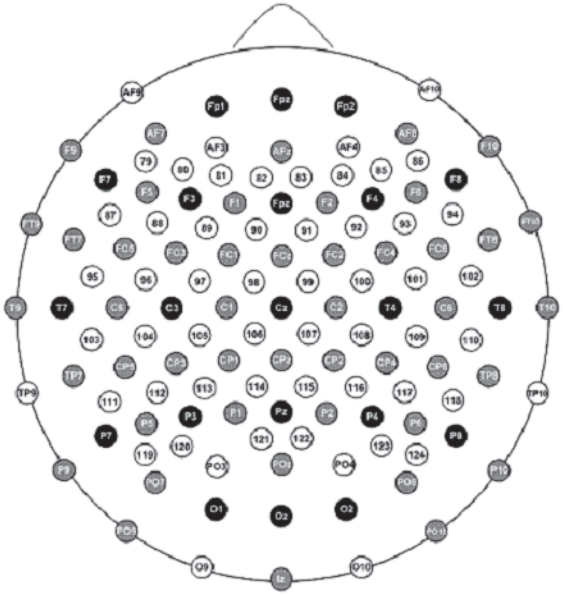

Figure 3: Probe locations in Net Station System 300

P300 signal. Basically, we would like to widen our search area over the whole surface of the brain. We used 128 probes Net Station System 300 for dense array EEG from Electrical Geodesics Inc., to collect EEG signals. It is equipped with 128 probes. The specified noise level is 0.7 μV RMS. A/D conversion resolution is 24 bit. Maximum sampling rate is 2000 Hz. Input impedance is 200 MΩ. In our experiments, we used a sampling rate of 1000 Hz.

The user interface is the same as used in conventional BCI speller, as shown in Fig. 1. Data were collected from healthy young subjects (students of age around 22). The experimental set-up is explained below. Our aim is to classify EEG signals in to two classes, to identify whether the signal contains ERP300 or not (Luck 2005).

Our equipment provides 128 probes as shown in Fig. 3. As analyzing 128 multivariate signals is computationally heavy, and as we want to cover the whole area of the head, we selected 21 probes whose locations are evenly spaced, and recommended by the International 10-20 system (Okuma 1999). It is shown in Fig 4. The space resolution of our data is thereby reduced.

The subjects are provided with the word to spell, so that we get a labeled set of supervised samples necessary to train a classifier.

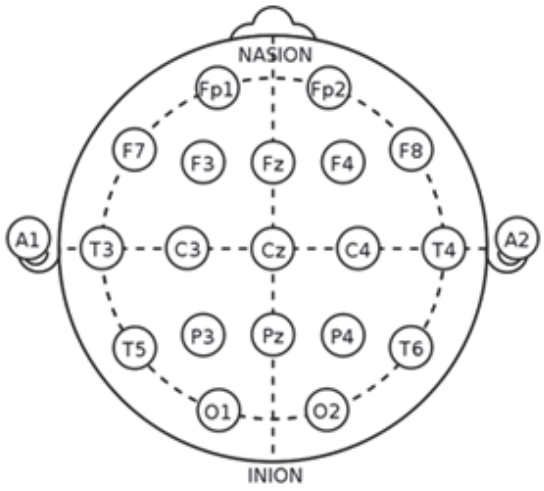

Figure 4: Electrodes from which EEG data were collected.

Proposed Algorithm

As a subject spells a letter, we collect 10 EEG signals corresponding to each row and column, corresponding to 10 flashes. In total we get 120 EEG signals from 21 probes, each of length 600 miliseconds. 20 such signals, collected while the target letter is included in the row or column, are labelled as containing P300. The rest 100 are signals without P300. We analyzed individual subject's data separately. Data collected from a single subject is separated into train and test data. Finally, a 5-fold validation is done to show the accuracy of the algorithm.

Preprocessing of the EEG data

EEG data contains high frequency noise from the environment. By using band-pass filter with a frequency band of 0.1 Hz. to 13 Hz., we clean the high frequency and DC noise. The upper band is set at 13 Hz, which includes the slow rising P300 as well as α, θ and δ waves. To eliminate spurious signals, the data is smoothed using moving average, and finally 10 signals collected at a probe while a particular row or column is flashed, are averaged. Thus, from every probe, for a particular letter, we get 12 data of which 2 contains P300. This is a standard procedure to filter out short spurious pulses due to random brain activities. Other artifacts,

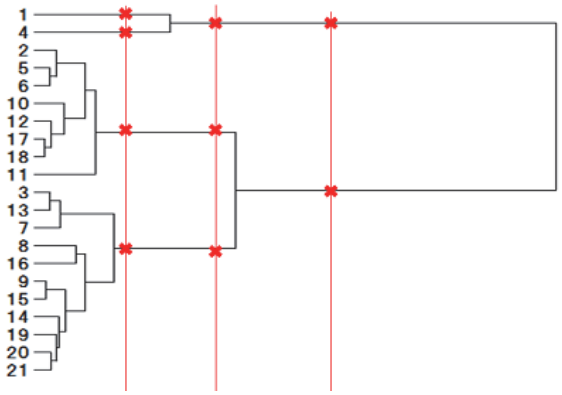

Figure 5: Dendrogram of Clustering result

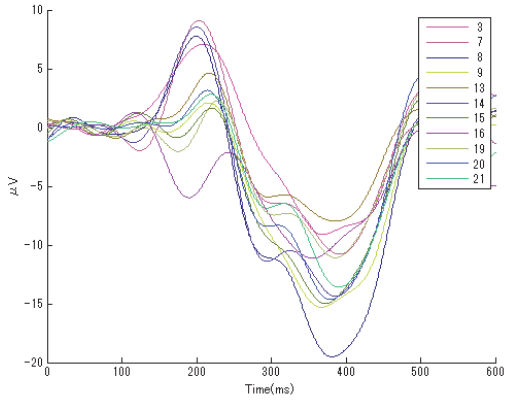

Figure 6: Quite different Signals are grouped in one cluster, when the number of clusters is low

due to facial muscle movement and eye blinking are cleaned by embeded software came with the system. In the next step, for clustering the data collected from different probes, we used Euclidean distances. For effective clustering based on the signal shape, we need to normalize the signals. For normalization, used linear pulse code modulation (LPCM), with 8 levels (Goodall 1947). At the time of feature extraction for classification, signals before normalization is used, because strength of the P300 signal is used as a feature.

Distance Metric Between Signals and Clustering of Signals from Different Probes

After normalizing, signals from 21 channels are clustered. The time delay from stimulus to occurance of P300 varies a little over the different regions of the scalp. The motivation of clustering is to put signals of similar shape in one group. In our previous work (Yokoha, Chakraborty, and Kikuchi 2014), Euclidean distances between signals were used for clustering. Here, distances between pre-processed normalized signals are calculated using dynamic time warping (DTW) algorithm. This ensures that signals of similar shape, though with certain time delay, will have low distance and would be clustered in the same group.

Using DTW distances, signals are clustered by Ward's algorithm (Ward 1963), a top-down agglomerative algorithm. The purpose of choosing top-down algorithm is that, we can set a threshold for the inter cluster distances and thus tune the number of clusters visually, using dendrogram. In Fig. 5 it is shown how the number of clusters could be chosen as 2 or 3 or 4, by adjusting the inter-cluster distances. In our experiments, we used 8 clusters. From each cluster a single probe with strongest P300 signal is selected. Number of clusters is set to 8 because: (1) we visually checked that then the members of each cluster have similar shapes. With lower number of clusters, like 4, even quite different signals are clubbed together, as shown in Fig.6. A typical signal cluster, when 21 signals are divided in to 8 clusters, is shown in Fig. 7. (2) Finally, we need to select the optimum set of probes. If the number of clusters is too high, searching for the optimum set will be a complex combinatorial problem.

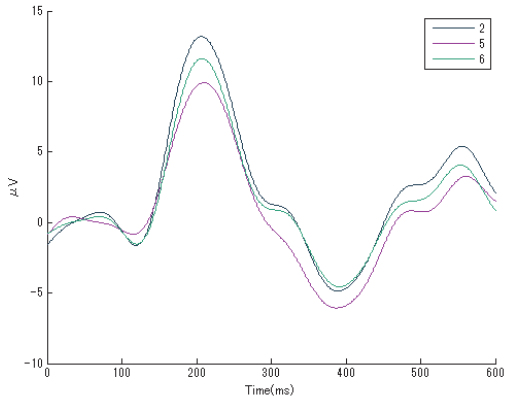

Figure 7: Member signals of a typical cluster group, when signals from 21 probes are divided into 8 clusters.

Selection of a Representative from each Cluster

Next, we need to select a representative from each cluster. We select the one for which the change in potential is highest. This is explained in Fig. 8. There are 3 members in the cluster. We measure the largest difference of potential for each member of the cluster. That is the score for an individual member. The member with highest score is selected as the representative of the group.

Multiobjective Optimization for Probe Selection

Our aim is to select minimum number of probes that would give the highest classification accuracy. After selecting representatives from each cluster, we have 8 EEG signals from 8 clusters. We need to find the minimum subset of these 8-probes which would give highest classification result. This is a multiobjective optimization problem. Though the search space is small, only $2^8 - 1$, we will use MultiObjective Genetic Algorithm (MOGA). Here, the fitnesses of two objectives are summed (after proper normalization) to calculate overall fitness. We will compare the results with exhaustive

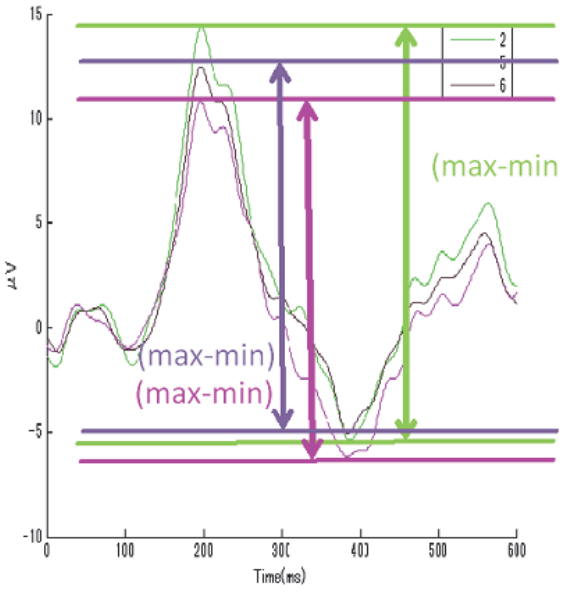

Figure 8: Cluster representative selection and signal feature extraction

search to investigate the effectiveness of MOGA. In our future work, we would like to expand the search space when exhaustive search will be too complex to finish searching in a reasonable time.

The problem is easy to code in GA. Chromosomes with 8 binary units are used. A gene with 1 represents that that probe is selected, whereas a 0 represents it is not. 2-point crossover is used, with crossover probability 0.5. Mutation is used with 0.01 probability. Tournament selection is used.

Feature Selection, Classification and Chromosome Fitness Calculation

First, features from the selected signals, as described by the chromosome's genes, are extracted. From every signal we extract 2 features, the maximum difference of the potential and the difference of time for their occurrences. As shown in Fig 8, the signal with highest $(max - min)$ is selected. Suppose, the maximum has occured at time t_{max} and the minimum at t_{min}. Then the two features are $(max - min)$, and $(t_{max} - t_{min})$.

We have a set of labelled data from a subject, containing signals with and without P300. Now, every data has 2 features and 2 classes. An artificial neural network, trained using error back propagation, is used for the classifier.

Suppose a chromosome has three 1s and 5 zeros. In that case, six features are extracted from the three signals, for all the samples containing ERP300 and not containing ERP300. The samples are labeled. The classification error is one criterion of a chromosome's fitness. The other criterion is number of signals, which in this case is 3. Using these two criteria, rankings of all the chromosomes in the population are calculated according to multi-objective optimization algorithm. We use summation of the two criteria, the minimum is the fittest sample and will be ranked 1. We normalize the two criteria for equal weightage.

In the next section, we will compare the results of classification with our previous work reported in (Yokoha, Chakraborty, and Kikuchi 2014) and with Hoffman et.al. (Hoffmann and et.al. 2008). In (Yokoha, Chakraborty, and Kikuchi 2014) the number of probes were fixed to 4. In (Hoffman 2008) the number of probes were 4, 8, 16 and 32. We will compare results with 4 probes, as in our experiments we always had less than 4 probes. Finally, we will compare results with exhaustive search, and show that though with some subjects we could achieve very good results even with only 2 probes, that is not true with all subjects. From the results, it is evident that training for subjects to concentrate during experiment is an important prerequisite for successful classification with less number of probes.

Difference with Our Previous Work (Yokoha, Chakraborty, and Kikuchi 2014)

We compared results with our previous work reported in (Yokoha, Chakraborty, and Kikuchi 2014). The difference with the present work is as follows. In(Yokoha, Chakraborty, and Kikuchi 2014), Euclidean distances were used to calculate distance between signals, not DTW. In addition, the number of clusters was fixed to 4. Always, 4 probes one from each cluster were used for identification of P300. In the present work, we used 8 clusters, but selected the best subset from 8 probes, eight representatives one from each cluster.

Experimental Results and Comparison with Previous Works

We will compare our results with (Yokoha, Chakraborty, and Kikuchi 2014) and (Hoffmann and et.al. 2008). The same data set collected during our experiments was used. We also compare results with exhaustive search.

Parameters used in PatetoGA experiments.

- Population size : 20
- Length of the chromosome : 8(same as the number of clusters)
- Number of generations : 200
- Crossover: One point crossover with 0.5 crossover probability.
- Selection rule : Tournament selection

In the following table we compare the results of classification for data obtained from 6 subjects. The comparison is between present work, the work presented in (Yokoha, Chakraborty, and Kikuchi 2014) and with exhaustive search. We show the number of probes used and corresponding classification results.

Conclusion and Future Work

In this work, we showed that when relevant probes are selected for an individual, we can reduce the number of probes to as low as 2, yet achieve improved recognition. The location of probes will be different for different individual. Our algorithm consists of 2 important steps, clustering and

Table 1: Experimental Results

	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6
Present work						
#probes	3	3	3	2	2	2
Recognition rate	72%	65%	74%	71%	60%	65%
Results using (Yokoha, Chakraborty, and Kikuchi 2014)						
#probes	4	4	4	4	4	4
Recognition rate	59%	66%	75%	64%	49%	69%
Results using (Hoffmann and et.al. 2008)						
#probes	4	4	4	4	4	4
Recognition rate	57%	61%	69%	61%	48%	60%
Exhaustive search from 8 channels						
#probes	5	4	3	4	3	6
Recognition rate	73%	66%	75%	77%	63%	74%

selecting a member from each cluster, and finding the optimum combination of signals for highest recognition. We could achieve better recognition with fewer probes, with every subject.

We learnt that the recognition rate varies from subject to subject. As we follow results for all subjects, we conclude that recognition rate is high for a subject who participated in the experiment many times. Thus training is required to increase concentration during experiment, resulting in higher recognition rate. For persons whose only way to communication is BCI, would concentrate more. We can expect better results with such patients.

The whole idea is based on the fact that for an individual, the best probe locations, once found, will not change with time. At least with 2 subjects, we collected data over a period of more than a year and found that the locations are stable. Further research is necessary to decisively make this conclusion.

As the clustering algorithm is fast, in our next attempt we will use signals from all the 128 probes available. We hope, by identifying probe locations more accurately, we could get better classification result with even less number of probes.

At present, we are experimenting on reducing the time required to spell a character. There are several works with this motivation. They are divided into two categories, using rapid serial visual presentation (Acqualagna and Blankertz Nov 2011), and based on steady-state visual evoked potentials(Friman et al. 2007) (Nakanishi and et. al. 2014). Our approach is based on Steady-state visual evoked potentials (SSVEP) too. We use conventional BCI speller display, but flash two columns simultaneously with 2 colors and different frequencies. Similarly, two rows are flashed simultaneously. Combining the SSVEP signal with P300, we can improve both the speed of spelling as well as accuracy.

In future, we plan to use all probes, where search space will expand.

Acknowledgements

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