Modifying the Classic Peak Picking Technique Using a Fuzzy Multi Agent to Have an Accurate P300-based BCI

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Abstract

EEG-based brain computer interface (BCI) provides a new communication channel between the human brain and a computer. The classification of EEG data is an important task in EEG-based BCI. In this paper we present a new modification on classic "Peak Picking" to make a better detection for a specific pattern in EEG. The new method shows a significant improvement in P300 detection which is a common approach in BCI systems. The proposed model uses more than one scalp electrode and combines the outputs with a fuzzy technique, to detect P300 cognitive component.

Keywords: EEG, ERP, BCI, Peak Picking Method (PPM), Fuzzy Membership Functions

1 Introduction

One of the most interesting fields of current researches is to develop a machine that can communicate with a brain, directly. Many methods for discrimination between different mental and cognitive activities have been developed so far, like; many techniques such as feature extraction, feature selection and classification. Each of these methods has their own benefits and drawbacks that make their use totally case-dependent. BCI systems use different methods to communicate with human brain. One of the most common communication techniques is to find a specific pattern in scalp-recorded EEG; like P300, N400, and N170 or generally ERP components. Different methods have been proposed to find a specific pattern in EEG, some like template matching and peak picking are classical ones while other methods like using a feature extraction block in combination with a classifier are modern ones [1, 2, 3].

The aim of this study is to show that a modification in a classical method (Peak Picking) can yield good results for P300 detection. This modification is using a simple fuzzy multi-agent to vote for a final decision based on decisions made by some Peak Picking blocks for some scalp electrodes (Fig.1).

So, this paper is organized as follows. After this introduction, in part 2, the EEG data will be introduced. Then in part 3, a brief review over Peak Picking will show its efficiency for P300 detection. In part 4, the proposed model for the classifier will be introduced and used to show the benefit with new model. Finally in part 5, the conclusion will be made to show the efficiency of this modification.

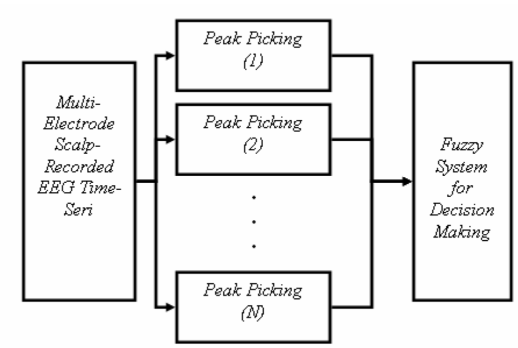

Figure1. Block diagram of the proposed classifier which comprises N template matching (TM) blocks and a fuzzy decision making system, (representing a typical multi-agent classifier)

2 EEG Data

In the present article, the EEG data is BCI Competetion2003 EEG dataset recorded from 64 scalp positions with P300 speller paradigm in which the subject was supposed to distinguish between two classes of stimuli; one class which contains a P300 cognitive component and the other one which lacks this component.

The aim of this competition is to detect the P300 component in scalp recorded EEG; which seems identical to our aim in P300 detection in this study. After data acquisition, there will be a 64 electrodes EEG data. Processing all these channels will be a time consuming task. So two important issues most be considered; 1) the efficiency in processing and 2) the classification accuracy. The first step to have an efficient classification is to know the scalp active regions during the P300 speller paradigm. In Fig.2, the average waveform for EEG data for a subject is shown for two classes of stimuli; with P300 (the upper panel, the dashed line) and without P300 (the upper panel, the solid line) for Cz electrode. The lower panel in Fig.2 shows the r value for these two classes of data. The r value (Eq.1) represents the difference between two classes of data with respect to time in which i is time sample, j is the trial number, and s is the EEG with P300, n is the EEG without P300.

(1) $$\mathrm{r}_{\mathrm{i,j}} = s_{i,j} - n_{i,j}$$

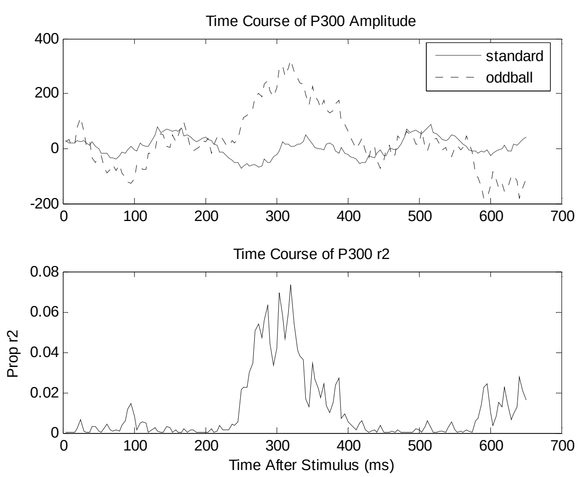

Figure2. (Upper panel) average EEG for two classes of stimuli over Cz electrode that shows a significant difference in about 300ms. (Lower panel) squared difference value (r) for each sample which confirms the importance of 300ms in class discrimination.

The r value shows that the major difference between two classes, happens around 300ms which is actually the time associated with P300 occurrence in the literature. Using plots in Fig.3, the major active regions during P300 occurrence can be estimated. This plot shows a head plot at 300ms after stimulus onset for one subject using all 64 scalp electrodes. Using this plot, it is easier to decide which electrodes to choose as the most efficient electrodes for P300 detection.

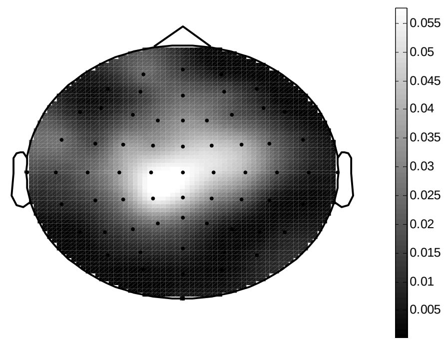

Figure3. The head plot for r value at 300ms after stimulus which can represent the activity at this time in head surface.

3 Using Classic Peak Picking for P300 Detection

As the name indicates, the aim of Peak Picking Method (PPM) is to detect a specific pattern based on its peak value in a region associated with a specific cognitive component. As far as the aim of this study is to use PPM for a P300 based BCI system, the aforementioned region is about 200 to 400ms which is the occurrence time of the P300 cognitive component. The mathematical background of this technique is quite simple and comprises a comparison between two values; a prespecified value (or the threshold) and a critical point's value (a point around 200-400).

If the point's value is bigger than this threshold, then the trial contains the P300 and if it's smaller than threshold, it doesn't contain the P300. In spite of its simplicity, this method yields good accuracy for a special P300 detection task; because of a dominant peak related to P300 occurrence around 300ms after stimuli onset [4].

Based on results from previous section, which adopted the time series values to show the active regions, it is obvious that using all 64 electrodes is not an efficient method. In addition to its long process time, this approach can cause a misclassification because of a bad detection in unrelated electrodes (like those near to Occipital or Parietal lobes).

As far as we need more than one scalp electrode for our modification, it seems necessary to find the best electrodes for a more accurate PPM based P300 detection. Before using PPM, data was preprocessed using band pass filtering (0.5-30Hz) which will cancel the high frequency noises and keep the ERP related frequency content of the trial. Using this technique on Fz, Cz, Pz, Oz, F3, F4, C3, C4, P3 and P4 electrodes the results (Table1) show that the accuracy for this technique is not acceptable (comparing with the results of new researches using modern techniques). The P300 detection process in a pseudo code step by step form is as follows;

1- Select a trial from an EEG dataset.
2- Filter this trial with a band-pass filter (0.5-30Hz) to cancel the high frequency content of the trial.
3- For the selected electrode, use a calibration to find its corresponding threshold value. The reason for this task is that the ERP over each electrode can have a different peak value and occurrence time.
4- Select the time samples from 250 to 350 and find the average value for them (for the BCI2003 data, this time interval will contain about 24 points). For this part a test was done for some other intervals that finally, this interval yielded the best result.
5- If the resulted average value is bigger than the threshold calculated in section3, the trial contains P300 and if not, then the trial doesn't contain this component.
6- Calculate the "Target Accuracy" and "Non-target Accuracy" and "Total Accuracy" for each electrode.

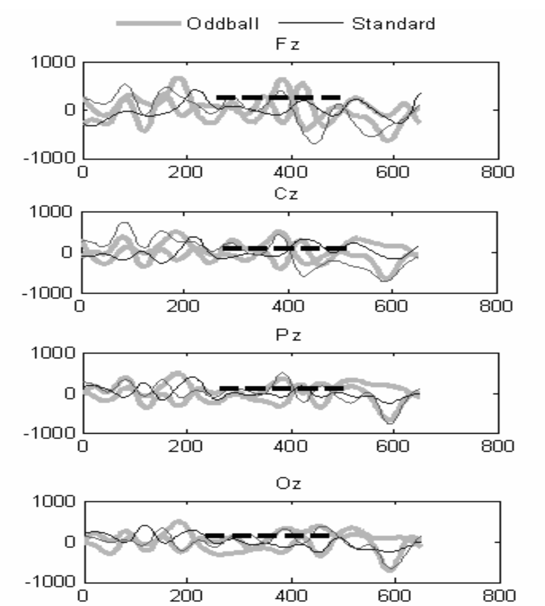

Figure4. Single trial plots for 4 scalp locations for target and non-target stimuli which indicate the difficulty with this method for an accurate P300 detection. The horizontal dashed bold lines show the threshold value.

According to percentage in columns 2 and 3 of Table1, it seems obvious that, for a specific trial, different channels can show different labels. This means that using a combination of outputs, based on the previous knowledge of the classifier, can make the results better. In the next section, using a fuzzy multi agent for this combination will be discussed.

Table 1: The accuracy for P300 detection using the classic PPM over some scalp electrodes (in percent) over 2000 trials (1000; target and 1000; non-target).

Electrode	Target Accuracy	Nontarget Accuracy	Total Accuracy
Fz	65.5	63.3	64.4
Cz	66.5	77	71.75
Oz	48.4	42.4	45.4
Pz	52.5	58.6	55.55
F3	61.3	60.5	60.9
F4	64.2	60	62.1
C3	67	70.6	68.8
C4	75.3	70.6	**72.95**
P3	52.6	55.6	54.6
P4	62	56.3	59.15

4 Modifying the Classic Peak Picking for P300 Detection

The spreading use of fuzzy logic shows its power in different task; specially inference and decision making. As shown in previous sections, a specific trial, can obtain different labels after going through each PPM block in Fig.1. This means that for each trial, some of PPM blocks can have accurate P300 detection while some others cannot.

In this section, we are going to modify PPM for a better and more accurate detection by simultaneously using it over some electrodes and voting over outputs to have a final label which will be better than a single PPM block. It seems to be a good idea to combine information acquired from different scalp positions to find the best combination for a more accurate classification [5].

For this reason, we used a fuzzy block as a voter or mixing block at the output to have all the PPM blocks' outputs as input to make the final output. As shown in Fig.5 and Table1, using a threshold based classification cannot yield good accuracy, at least for one scalp electrode. So it seems necessary to find a solution to combine the results from each electrode.

In this work, for good combination, the process was as follows. First of all, the classifier must get calibrated over a dataset (a train dataset). For training process, for each electrode we need a Max and Min value which represents the 0.95 and 0.05 of input range in Fig.6 respectively. Then using this Max and Min values, each average value (step 4 of previous section) must be normalized to a point between 0.05 and 0.95 (using Eq2).

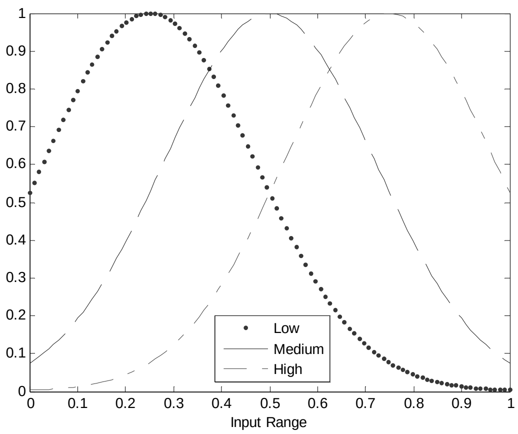

Figure6. Three Gaussian membership functions used to assign the outputs with a label; High, Low or Medium

$$NormVal = [\frac{(0.95)-(0.05)}{Max-Min} * (Val - Min)] + Min \qquad (2)$$

After doing all these operations, average value (step4 of previous section) will be a member of three rules in Fig.6 with a specific membership.

Having membership values for each trial over each electrode and the rules in Table2, the final label for the input trial will be determined. Because of poor accuracy of Oz, Pz, P3 and P4 electrodes, they will not be taken into consideration (so we will use only Cz, C3, C4, Fz, F3 and F4).

Using this technique, for the same input trials as what used for section2, the accuracy result is shown in Table3. As can be seen, the results are really better than the previous ones.

Rules in Table2 are extracted based on some experimental trial and error procedure. This table shows a reduced set of rules that were the most effective and accurate ones.

Table2. Fuzzy rules used to determine the final label of an input trial based on its TM output over electrodes Cz, C3, C4, Fz, F3, and F4.

Rule#	If	Then
01	Sum (High)>Sum(Low)	Label=High
02	Sum(Low)>Sum(High)	Label=Low
03	Sum(Low)=Sum(High) C3=C4=Cz=Medium	Label=Low
04	Sum(Low)=Sum(High) C3=C4≠Medium	Label=Label(C3)
05	Sum(Low)=Sum(High) C3=Cz≠Medium	Label=Label(C3)
06	Sum(Low)=Sum(High) Cz=C4≠Medium	Label=Label(Cz)
07	Sum(Low)=Sum(High) C3=C4≠Medium	Label=Label(C3)
08	Sum(Low)=Sum(High) C3=C4=Medium Cz≠Medium	Label=Label(Cz)
09	Sum(Low)=Sum(High) Cz=C3=Medium C4≠Medium	Label=Label(C4)
10	Sum(Low)=Sum(High) C4=Cz=Medium C3≠Medium	Label=Label(C3)

Table3. Accuracy values for final system (Fig.1) over 2000 trials (1000 target and 1000 non-target).

System	Target Accuracy	Nontarget Accuracy	Total Accuracy
TMs + Fuzzy Voter	81.2	78.1	79.65

5 Review of the Method for a Typical Stimulus

Now that everything is described for this method, in this part we will evaluate a sample trial to detect whether it contains the P300 or not. The following step will be done till the final output (label) gets determined:

1- A trial must be selected for a particular stimulus for electrodes Cz, C3, C4, Fz, F3 and F4.

2- All six trials from previous step must get filtered for a noise cancellation (0.5-30Hz band-pass filter).

3- The average of samples ranging from 250 to 350 must be calculated. If it is bigger than the Max, then it contains the P300 and if not, it will get normalized using Eq2.

4- The output of step3 must go for membership functions in Fig.6 to determine its membership for three rules.

5- It will yield six memberships for six electrodes that will determine the final label based on rules in Table2.

Following these steps, we will have a simple but fairly accurate method for P300 detection. The final accuracy of 79.65% over 2000 samples is a good result for a simple classification procedure like our modified PPM.

6 Conclusion and Discussion

In this study, we used a new technique to modify a simple classification technique like Peak Picking. As shown in results, the poor PPM results got much better by a simple combination based on a fuzzy rule set. This idea can be used for better accuracy by combining some more accurate classifiers; such as SVM, LDA, ANN, etc.

The main advantage of this method that caused such good results was to combine information from different scalp places for a better classification.

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