# Classification of EEG based BCI signals imagined hand closing and opening

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### D. Classification Method

Statistical estimation and pattern recognition used in *k*-NN algorithm is an easy method that supplies all present cases and classifies new cases with similar measurements [16]. Hence, in this paper, we used *k*-NN method as classifier. This method classifies an unknown example with the most common class among *k* closest examples. For this classifier, though there are many types of distance measurement to calculate the distance of the neighbor(s), we used City block distance given in Equation 8, which is commonly used in literature. Here, this distance defined by between two points (6+ ) 75 cartesian coordinates) is the sum of the absolute difference. Then, in order to define the best value of *k*, we used leave-one-out cross-validation method to boost the classification performance. In this technique, *k* value was researched in the interval between 1 and 25 with step size of 1.

8+5 * : 96+: 7 5: 9 ;

We attained percentage of CA given in Equation 9, to evaluate performance of the *k*-NN classifier. While <· is the number of correctly classified trials, =· is the total number of considered trials.

<= >? / @? AA (9)

LDA is a classification method developed by R. A. Fischer in 1936. This method was used for two or more classes data set and found a linear combination of features .Additionally, in order to show the effectiveness of the k-NN classifier, we also tested the extracted features by commonly used LDA classifier. It is worthwhile mentioning that because k-NN classifier achieved higher classifier, we did not introduce LDA classifier in detail.

## III. Results and Conclusion

In this study, EEG trials, recorded from 29 people, were firstly pre-processed with MAF. Afterwards, HT and MD based features were extracted from pre-processed EEG trials. Finally, the extracted features were tested by *k*-NN and LDA classifiers. The same procedures were also performed for the unprocessed EEG signals to exhibit the effectiveness of MAF. The results were calculated by cross-validation analysis over 50-times run on the EEG data set. It is worthwhile noticing that B'C and D'C electrodes were selected as effective electrodes with this analysis.

For *k*-NN classifier, average CAs calculated over 50-times run for each person with pre-processing and without pre-processing were given as radar graph in Figure 2. In this graph, while the highest CA was achieved as 92.73% for Subject 2, minimum CA was obtained as 67.46% for Subject 20 with pre-processed EEG data set. Furthermore, the average CA of 29 subjects was calculated as 82.23% and 69.45% for the pre-processed and unprocessed EEG data set, respectively.

Figure 2. CAs calculated from 29 subjects with pre-processed and unprocessed EEG data set for *k*-NN

On the radar graph, while circles define CAs from 0.00% to 100.00%, each line dividing these circles indicates all subjects from 1 to 29 and the subjects are specified by E ) E ) EF) G G G G G E DG

Figure 3. CAs calculated from 29 subjects with pre-processed and unprocessed EEG data set for LDA

Morever, to show the effectiveness of *k*-NN classifier for this data set, CAs, based on the same validation procedure, were also calculated by LDA for 29 subjects over 50-times run given in Figure 3. As it is seen in Figure 3, the average CAs were calculated as 78.13% and 59.19% for the pre-processed and unprocessed EEG data set, respectively. Furthermore, it emphasized that Figure 2 indicated uniform distribution compared to Figure 3 for all Subjects. The average 82.23% CA calculated by the *k*-NN is 4.10% higher than by the LDA with pre-processed EEG data set. Hence, it can be stated that the *k*-NN classifier is more suitable and effective for this study. For this effective classifier, we calculated the average confusion matrix of all subjects as percent with pre-processed EEG data set, as given Table 1. As seen in the Table, class 0 and class 1 were correctly labeled as 76.13% and 88.33% respectively. On the other hand, while 23.86% class 0 was labeled as class 1, 11.66% class 1 was labeled as class 0.

TABLE I. CONFUSION MATRIX FOR K-NN

| **Confusion Matrix** | | **Predicted Class** | |
|---|---|---|---|
| | | Class 0 | Class 1 |
| **True Class** | Class 0 | 76.13% | 11.66% |
| | Class 1 | 23.86% | 88.33% |

Furthermore, we calculated Sensitivity (SE) and Specificity (SP) as percent for all subjects with pre-processed EEG data set for *k*-NN in given Figure 4. While the average SE of all subjects was obtained as 76.13%, the average SP of all subjects was calculated as 88.33%.

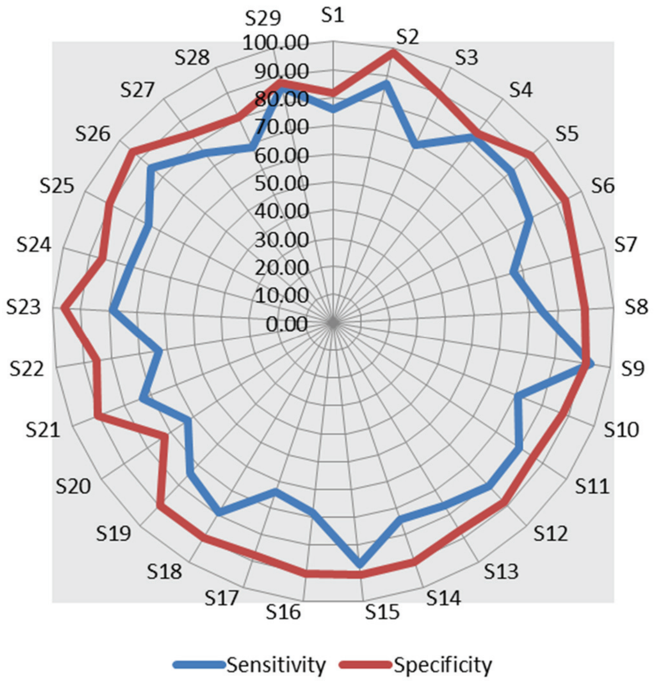


Figure 4. SEs and SPs with pre-processed EEG data set for *k*-NN

In this study, the proposed method was succesfully applied to all subjects with high CA performance. Finally, we believe that the suggested method could largely contribute to the classification of EEG signals recorded during imagination of opening/closing hand movement. Another contribution of the proposed method is that it can be generally applied to all subjects. That is, it does not individually require any tune parameters.

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