Using EEG Signals to Detect Different Surfaces While Walking

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Abstract. Brain-Computer Interfaces are one of the most interesting ways to work in rehabilitation and assistance programs to people who have problems in their lower limb to march. This paper presents evidence by means of statistical analysis sets that there are specific frequencies ranges on EEG signals while walking on four different surfaces: hard floor, soft floor, ramp and stairs, finding proportional differences in predictions between each pair of tasks for every user through the employ of Matlab classifiers. In that way, our results are statistical sets of successful percentages in classification of signals between two tasks. We worked with five different volunteers and we found an average of 76.5% of success in predictions between soft floor and stairs surfaces. Lower results, around 60%, were obtained when differentiating between hard floor/stairs and ramp/stairs. We can notice that magnitude of these percentages fits with a common sense about real physical differences between four kinds of surfaces. This study means a starting point to go deeper in signal morphology analyzing the specific mathematical characteristics of EEG signals while walking on those surfaces and other ones.

Keywords: Surface detection · EEG Signals · BCI Systems · Walking

1 Introduction

Nowadays computing technologies are increasing fast and strongly due to global spreading of demand in almost every way of human management tasks [1]. One of those fields of study is the design and development of brain-computer interface (BCI) in order to support people who have dysfunctional problems to walk, because of physical injuries in their lower limb, through fit mechanical exoskeletons able to lead movements of muscles to make them strong and functional in the fastest, effective and cheapest programs of rehabilitation [2–7].

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In relation with rehabilitation, several studies have been performed in order to get patients more implicated into their therapies. For example, detection the intention of starting or stopping gait [8,9] or detection the attention paid to walk [10], so rehabilitation therapy can be modified to help more the patient. Moreover, detecting unexpected obstacles can improve safety while working with exoskeletons [11].

This study line works to endue these exoskeletons capability to adapt their mechanical configuration to any kind of surface which user had intention to walk through before he/she steps in by just reading his/her EEG signals, anticipating changes to get the system ready to new walking conditions in the softest way. This objective implies two great development phases: identifying states and tendencies of EEG signal morphology as a function of surface characteristics and implementing that knowledge in exoskeletons controlled by BCI systems with correct responses in every way and an appropriate real time working. This paper presents the most primitive work in which we simply show by statistical analysis that EEG signals walking on a certain surface may high probably have a core morphology related with that surface characteristics in order to be this study the green light to approach EEG signals morphology and the development of the project in general.

2 System Architecture

Experimental tasks consisted in a series of EEG signals registered while walking in different surfaces. There were four different ones: a hard floor, a soft floor, a ramp and stairs. One register file from a user contains data of four tasks, each one corresponding to a different surface.

2.1 Acquisition and Users

Five users with ages between 14 and 25 years old perform the experiments. EEG signals were recorded with the actiCHamp equipment from Brain-Products Company. It allows registering 31 electrodes placed on the scalp following the 10/10 International System. The frequency sample was 500 Hz. They were placed in next positions: FZ, FC5, FC1, FCZ, FC2, FC6, C3, CZ, C4, CP5, CP1, CP2, CP6, P3, PZ, P4, PO7, PO3, PO4, PO8, FC3, FC4, C5, C1, C2, C6, CP3, CPZ, CP4 and P1. The reference was placed on right ear lobe. The equipment allows sending the information to the computer by a wireless connection through the MOVE module. This was an important issue to allow the user climbing stairs.

2.2 Experimental Procedure

After placing the cap to register EEG signals, the users are asked to walk through the four different surfaces. First the hard floor, then the soft floor, next the ramp, and finally the stairs. User last around 7 s walking through each different surface. Users repeat the same process 20 times. Figure 1 shows the environment where the user performs the experiments.

Fig. 1. Environment where users perform the experiments. The four different surfaces are shown: hard floor, soft floor, ramp and stairs.

2.3 Processing

The software was developed in Matlab. EEG registered signals had segments of invalid data due to failures of communication between emitter and receiver in wireless acquisition device during registering. Thus, an initial procedure was performed to clean registers by means of cutting off those parts of invalid data. Secondly, once registers are ready, they are processed in order to extract proper features to run the classification phase. For each clean user register, the program divides the total length into small segments overlapped. Then, a Fourier transform is calculated for each segment to get a simple feature for each task: a geometric mean of power spectrum amplitude in a specific frequencies range for all 31 electrode data arrays and an arithmetic mean of those 31 values. In this point, once processed and consequently to this study, for each register its built a matrix with 4 columns: first one with features for theta rhythm (3 to 7 hz), second one for alpha rhythm (8 to 14 Hz), third one for beta rhythm (14 to 31 Hz) and the last one contains the task number 1 to 4 associated to the row. The number of rows was different for each register depending on the number of overlapped segments, which in turn depends directly on the time length of registering which is slightly variable between registers and users.

2.4 Classification

A classification stage has been developed to determine which field of data a new set belongs to. One features matrix has the processed information of one register.

Classification employs all the registers of one user, just one user once, so what we give to it to be worked for each user is a matrices array as long as number of registers he/she has processed. For most part of user feature data, this number of processed registers is 20, so we introduced an array of 20 features matrices to classify in all cases excepting one in which we just used 19 because one of the registers was corrupt.

The algorithm of classification is based on creating models using all features matrices except one which is later employed to test the model, that is a cross-validation. Creating models is a process called training.

Classification, both for training and for testing, is run by classifiers, which are more or less complex mathematical algorithms implemented on computing program that are able to train and test data. We employed 5 different classifiers to get a large map of results where to observe the best ones and select more successful classifiers to analyze its inner logic in order to study the morphology of surface walking EEG signals in later studies. Best results were provided by classifier Nearest Neighbor. The rest of classifiers employed were Support Vector Machine, Naive-Bayes, Regression Trees and Lineal Discriminant Analysis.

So as to get best quality and accuracy in our results, due to statistic nature of this study, we did a cross validation, that means testing all the 20 feature matrices individually on 20 different models built every time with all the rest of matrices. In such a way, we got a wide number of predictions so our general result values as success likelihoods got consistence.

As we said before, the program process and classify all the registers of one user. Furthermore, classification was always run in pairs, which means that data sets to test are sort in one class between two options. Thus, as there are four tasks submitted to study there are six possible pairs, so the program simultaneously generates six different training models to test six times every testing register. In this way, the program obtains six large columns with all its predictions between two different tasks, so finally results are calculated just comparing done predictions with real corresponding task numbers.

3 Results

Several analysis were performed with the registered data. Theta, alpha and beta rhythms were calculated independently. Also, 3 different overlaps and 4 sizes segments were analyzed. All possible combination of parameters was processed. Table 1 summarizes the best average results for each user indicating the classifier applied, and the size segment, overlap and rhythm used. For each user 960 values were computed.

Its observed that most successful classifier, as we already said, is Nearest Neighbor. Once best average results are showed, we proceed to present the parts that compose those average values, it is mean, the likelihood values of success in classification in each of six specific pair of tasks. Results are shown in Table 2.

We can observe that for all users those results show maximum values for predictions in which walking upstairs is one of the two compared tasks. In three cases R/S has the higher value, followed closely by both Hard and Soft Floor tasks. The other two cases present high similar value in these three predictions. We can also notice that predictions between two Floor tasks and the Ramp one are quite lower than stairs predictions. However for most part of users these values are close to 60%, which is a higher value than predictions between Hard and Soft Floor that have no auspicious percentages.

Table 1. Best results obtained for each user. NN: Nearest Neighbor.

	Success rate (%)	Classifier	Size	Overlap	Rhythm
User 1	62.5	NN	2000	250	Alpha
User 2	64.7	NN	2000	400	Multirr.
User 3	74.3	NN	2000	250	Theta
User 4	62.4	NN	2000	250	Beta
User 5	66.9	NN	2000	400	Alpha

Table 2. Specific results for each pair of tasks (%). HF: Hard Floor; SF: Soft Floor; R: Ramp; S: Stairs.

	Success rate (%)	HF/SF	HF/R	HF/S	SF/R	SF/S	R/S
User 1	62.5	46.8	50.1	72.2	53.7	73.4	72.0
User 2	64.7	43.1	61.2	78.2	58.7	75.7	69.1
User 3	74.3	54.3	68.8	80.5	64.2	80.5	86.2
User 4	62.4	47.4	48.7	77.5	52.8	77.6	79.5
User 5	66.9	54.7	57.1	79.2	62.1	72.3	81.8

4 Conclusions

In this work the EEG signals of user that walks through different surfaces has been analyzed. Most significative point to highlight in results of this study are that values of six predictions have proportional relation for all user: HF/SF are in all cases the lowest value, HF/R and SF/R the medium value and HF/S, SF/S and R/S the highest values. We also consider meaningful the fact that these magnitudes differentiating two tasks by processing EEG signals employing classifiers fit with the difference grade that we could appreciate between tasks with a naked eye.

The results of this study evidence that walking on a specific surface reflects specific EEG signals univocally associated with that task, so in future studies we could go deeper analyzing those signals mathematically to find characteristic EEG signal morphologies relative to type and characteristics of different surfaces. Moreover, the procedure will be improved to be able to differentiate between the four different surfaces simultaneously and online experiments will be performed. These findings will contribute to adapt quickly the mechanics of lower limb exoskeletons for rehabilitation just reading EEG signals.

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