Use of Topological Data Analysis in Motor Intention Based Brain-Computer Interfaces

Fatih Altindis
Dept. of Electrical-Electronics Eng.
Abdullah Gul University
Kayseri, Turkey
fatih.altindis@agu.edu.tr

Bulent Yilmaz
Dept. of Electrical-Electronics Eng.
Abdullah Gul University
Kayseri, Turkey
bulent.yilmaz@agu.edu.tr

Sergey Borisenok
Dept. of Electrical-Electronics Eng.
Abdullah Gul University
Kayseri, Turkey
sergey.borisenok@agu.edu.tr

Kutay Icoz
Dept. of Electrical-Electronics Eng.
Abdullah Gul University
Kayseri, Turkey
kutay.icoz@agu.edu.tr

***Abstract*—This study aims to investigate the use of topological data analysis in electroencephalography (EEG) based on brain-computer interface (BCI) applications. Our study focused on extracting topological features of EEG signals obtained from the motor cortex area of the brain. EEG signals from 8 subjects were used for forming data point clouds with a real-time simulation scenario and then each cloud was processed with JPlex toolbox in order to find out corresponding Betti numbers. These numbers represent the topological structure of the point data cloud related to the persistent homologies, which differ for different motor activity tasks. The estimated Betti numbers has been used as features in k-NN classifier to discriminate left or right hand motor intentions.**

***Keywords*—EEG, brain-computer interfaces, topological data analysis, motor intention waves, JPlex**

I. Introduction

Brain-computer interfaces (BCIs) are used to help patients, who have less or no control over their motor neurons, such as ALS or lock-in syndrome patients [1]. BCIs interpret and extract meaningful information from the brain activity measurements that are related to motor activities, and help patients to regain their motor abilities or communicate with their environment [2]–[4]. BCI technology acquires brain activity information either directly from the patient's brain cortex with multichannel electrodes (electrocorticography, ECoG) or over patient's scalp surface with multichannel electrodes (electroencephalography, EEG) [5]. Until now, different BCI systems have been developed, such as moving the cursor on the screen, sending messages or turning lights on or off [6]–[10]. In this work, we will focus on EEG based BCIs due to their noninvasive nature.

Motor intention (MI) based BCIs aim to control or start an action by processing EEG signals and by extracting information during a voluntary movement intention period of extremities. A change in the EEG signals of the individual takes place before the actual motor activity begins [11]. MI based BCI systems widely use band power changes in specific frequency bands. Mu waves are specific brain waves that show up mostly at posterior, parietal and premotor cortex of the brain during resting [12], [13]. Mu waves oscillate between 7.5 - 12.5 Hz and it dramatically decreases during motor intention or motor activity due to the desynchronization of neurons, which is called as the event related desynchronization (ERD) and indicates the motor intention activity [14]–[16]. Moreover, motor cortex neurons synchronize and lead to EEG signals oscillating between 15–30 Hz during the motor intention activity. The synchronization is referred to as the event related synchronization (ERS). The waves in this frequency range are beta waves [17], [18]. The power changes in the mu and beta bands are calculated and motor intention activity is detected in MI based BCI systems. However, this approach is very sensitive to noise components, and needs a preprocessing step.

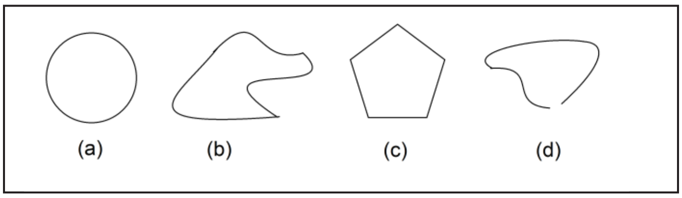

Fig. 1. Example of a topological analysis. First three shapes (a, b, c) have the same topology, but last one (d) is topologically different from others.

Topological data analysis (TDA) is one of the fastest developing branches of mathematics, which basically investigates geometric similarities of point clouds. TDA interpretations use different homology properties such as connectivity, surface, edge and volume [19]. This approach enables robust, fast and functional analysis of large datasets like EEG recordings [20], [21]. Fig. 1 shows how topological analysis interprets shapes. Topological parameters (connectivity, surface, hole etc.) are represented by special numbers called 'Betti numbers' (β_n). For instance, the number of connected point groups (connectivity) is represented by Betti0 (β_0), and the surfaces are represented by Betti1 (β_1) numbers. Betti numbers are evaluated over time by Rips stream analysis [22]. This analysis shows persistency of Betti numbers and persistent homologies are used to determine point cloud shape. In this study, TDA is used for analyzing EEG

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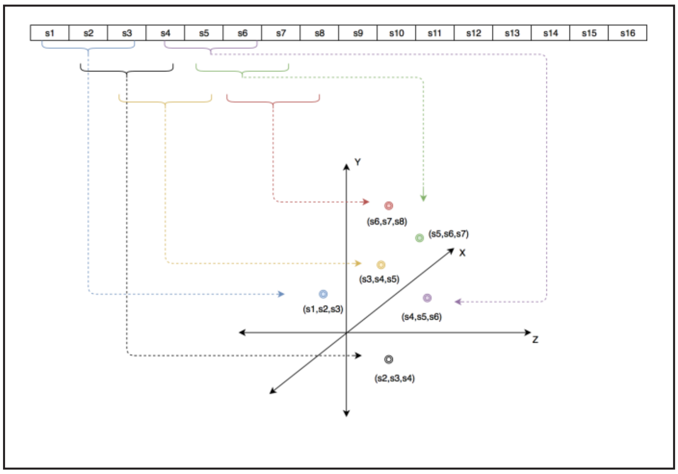

Fig. 2. This figure represents the formation of three-dimensional point cloud, from a one-dimensional data. s1 to s16 are data samples.

signals to develop an alternative MI based BCI system due to its robustness to noise.

II. Material and Methods

A. Dataset and JPlex Toolbox

In this study, an EEG dataset created by Graz University, Austria, for the BCI competition in 2008 was used [23]. This dataset is publicly available and includes EEG recordings of 8 subjects. Each subject imagined 120 right and 120 left hand movements during the experiments. The imagination here is called "motor intention." A total of 240 hand movement imaginations were acquired from each subject. EEG recordings were taken from the C3, Cz and C4 electrodes with a 250 Hz sampling rate. The electrodes were placed on the scalp of the subjects according to the international 10-20 system. The experimental paradigm started with a resting period of 3 seconds, which was followed by a cue shown on the screen. The subject started to imagine a hand movement from the 4th to 7th second. A 2-second relaxation period was the final action in each trial. This paradigm was repeated by the subjects for all trials.

EEG recordings were processed on MATLAB 2016a using JPlex toolbox [24]. JPlex is a specific toolbox, which was developed in order to perform persistent homology analysis on a given set of data. It has been used in many studies in the topological analysis field [25], [26].

B. Signal Processing

As we know, each EEG channel contains one-dimensional (1-D) data, however, a multidimensional data is needed for forming a point cloud to be in topological data analysis [27]. Thus, a specific path was followed in order to create point clouds from the EEG signals of single electrode channel. Formation of the point cloud starts with the determination of the dimension of the point cloud.

In our study, we used a moving window, whose width was equal to the predetermined dimension value, to form the point cloud. Each data sample within the window was used as the coordinate value of each dimension. Then, the window was shifted one sample to the right, and the same operation was repeated until the last sample on the signal. This technique is called 'delay embedding' [28], [29] and it enabled us to create multidimensional point cloud from 1-D data. Briefly, when the signal had N samples and the data cloud had D dimensions, the moving window had a D-sample width. The window started from the beginning of the signal, and the first sample corresponded to the first coordinate value, second sample corresponded to second coordinate value, and so on. Thus, a point in the space (point cloud) with D coordinate values was formed. Then, the window was shifted by one sample, and the second point was formed. By this way, N-D+1 points in the data cloud were formed from an N sample EEG channel with 1 sample delay (1). Fig. 2 explains this procedure visually.

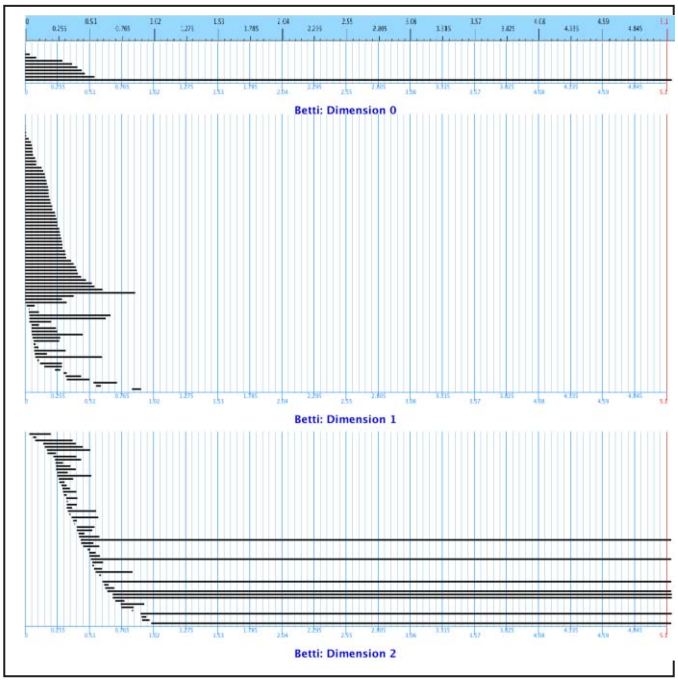

Fig. 3. Betti barcodes represent each individual topological shape. Lengths of the bars show their lifetime, and persistency of those homologies depends on length of these bars.

$$M_{cloud} = N_{data} - D_{dimension} + 1 \quad (1)$$

In this study we simulated a real-time BCI application by using a previously recorded multichannel EEG data. For this purpose, we processed 1-second data in each iteration and updated the data every 200 milliseconds. After obtaining the new chunk we again processed the last 1-second data in the next iteration. As it is mentioned in the previous section, the actual sampling rate was 250 Hz, thus the analysis began with the first 250 samples, and moved 50 samples in each iteration until it reached to end of the EEG data. This approach allowed us to analyze EEG signal epoch-wise, and thus, to observe any topological changes during the process.

After the formation of the point cloud, the topological analysis began with the witness stream approach. In this approach, first we chose 'L' landmark points from 'M' points

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of the point cloud and measured the points' distribution in space. Then, these landmark points were assumed as spheres to start stream analysis. Their radii were increased by 'lambda' (λ). The number of vertices, edges and holes were counted in each step, when the radiuses of landmark points were increased. These numbers were represented by Betti numbers [30]. Remaining points of the point cloud, besides the landmark points, witnessed every appearance and disappearance of edges and holes. Increasing the lambda value proceeded until all the landmarks cover 10% of the whole point cloud. This process was repeated on each epoch of the EEG signal, and the Betti numbers of each epoch represented persistent homology of that epoch.

The EEG signals we used were processed by following this technique. Each channel (C3, Cz, C4) was analyzed separately. For each EEG channel, 1-second epochs with 800 ms overlap were formed, and 5, 6 and 7-dimensional point clouds were created using delay embedding for each epoch. Topological analysis of these epochs was completed with the witness stream technique explained above. Betti number evaluation of a single channel was shown as barcodes as shown in Fig. 3. Barcode graphics demonstrated the lambda values of the appearance and disappearance of every edge and hole. Longer bars indicated the persistency of the corresponding hole, which meant that there was important information. Because, the characteristic signals created more determined shapes in space, and they formed stronger homologies. On the other hand, the noise in the signal appeared and disappeared in shorter lambda periods, because they have inconsistent structure in space. Thus, shorter bars in barcode graphics mostly implied the noise.

C. *Feature Set and Classification*

The topological analysis of EEG signals returned Betti numbers corresponding to each epoch. These Betti numbers were used to create a feature set for each imagery hand movement trial. Betti numbers coming from the rest period were divided by the numbers coming from the imagery period, which served as features for EEG trials. For each subject, there were 120 right and 120 left hand imagery movement trials. Three different approaches were used for the construction of the feature set and each approach was evaluated separately. The first approach used ratios of Betti numbers computed during rest and imagery periods. The second approach used only the imagery period of the EEG recordings. The feature set was formed using average Betti number values of each imagery period of each imagery hand movement trial. The last approach used the Betti number ratios between C3 and C4 channels during imagery hand movement periods and Cz channel excluded in the last approach. Then, the features obtained using these three approaches were combined and evaluated again.

Feature sets were used as the input in MATLAB Classification Learner toolbox for classification. Left or right hand imagery movement was assigned a label as 0 or 1, respectively. A 10-fold cross-validation was performed, and all the classification methods available in this toolbox were investigated in the classification phase. However, only the accuracy results from the k-NN method were shared in this paper due to its good performance. Classification performances were converted using Cohen's kappa conversion in order to compare our results [31], [32].

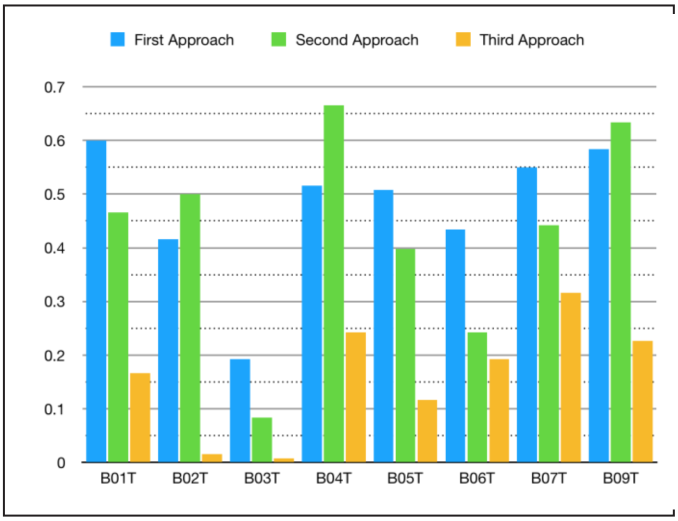

Fig. 4. Results of each approach showed.

III. RESULTS

Fig. 4 shows the performances for each subject separately obtained using three feature extraction methodologies mentioned above. Actually, the first approach followed a similar approach that is generally used for calculating ERD/ERS in EEG signals. However, in our work, we employed the Betti numbers instead of band power values. Thus, topological structure changes between periods were compared in order to detect hand movement imagination. The accuracies were mostly around 0.5 kappa.

The second approach focused on the individual topological complexity of EEG of each electrode during motor imagery period. The combination of features obtained using two approaches explained above was used in order to increase the classification performance. The classification performances of three combinations (1 and 2, 1 and 3, 2 and 3) were shared in the Table I. Finally, all features were combined, and the classification performances were shown in Table I.

The classification results of topological analysis of EEG signals showed that the EEG signals' topological structure differs during imagination of motor activity. Fig. 4 shows that first and second approaches provide best results for the classification of the left and right hand imagery movements. The first approach used topological difference between resting state and imagery periods, and the results depicted that the topological features of the resting state and imagery periods were different. In addition, this approach showed that the difference in the ratio between resting state and imaginary period varied from channel to channel. It is known that mu and beta band powers change during motor activities, and the topological analysis showed that topological structure of EEG signals in space also changed during motor activities. However, the main difference here is that topological analysis does not need any preprocessing or filtering.

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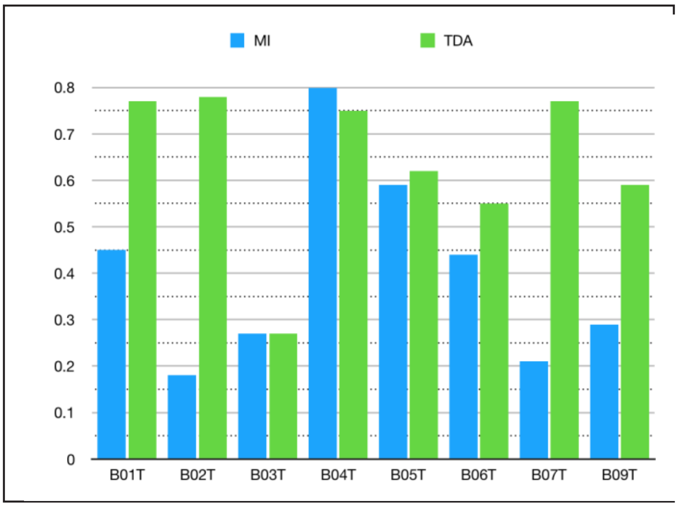

Fig. 5. Motor intention wave based and topological analysis methods were compared. The accuracies are shown for each subject.

The results of the second approach indicated that the topological structure of imagery motor movement period was different for each channel. For example, if the subject imagined right hand movement, C3 and C4 channels that are related to the real or imagery right and left hand movements, respectively. When topological analysis was applied on both of these channels, the topological structure of the EEG signals coming from C3 differed from the structure from the C4. The combined feature sets using first and second approaches gave slightly better results obtained with the methods used alone.

Finally, the results of the topological data analysis was compared with a motor intention band power based method [33].

Topological analysis approach resulted in better performances for detecting imagery hand movement from EEG signal. Fig. 5 shows that the classification performances increased for most of the subjects.

IV. Discussion and Conclusions

In this study, a new approach has been proposed to analyze EEG signals for the motor intention based BCIs. The study focused on differences and characteristics of EEG signals from a topological view. We developed a topological data analysis approach for extracting features from the signals and compared it with the band power based motor intention EEG analysis. EEG signals were taken from the channels that were the closest to the motor cortex of the brain.

We should note that the point cloud formation is a crucial step for the TDA approach, since all the vertices and holes are formed according to the location of the points in the cloud. Proposed method allowed us to use 1-D signals for the data analysis. Moreover, there is no need for filtering or denoising before the point cloud formation. TDA method demonstrates high robustness and stability under the noisy perturbation of the data set. This is the main advantage of the topological data analysis method and it simplifies the signal processing dramatically.

However, if the point cloud had high dimensional space, or the point cloud had too many points to analyze, then the evaluation of the point cloud slowed down exponentially. In addition, if the parameter lambda was increased to cover the whole point cloud space, the evaluation of that space, again, slowed down. Furthermore, these conditions required increased processing power in order to perform the topological analysis, due to design of the toolbox used in this study called JPlex. Although JPlex is the most recommended and reliable toolbox that is available for topological analysis, it still needs improvements for deeper analysis, but this was beyond the scope of our study.

In this study, we showed that the topological analysis of EEG signals might provide valuable information for the BCIs. Topological analysis is a robust and insensitive method against noise, which eliminates the preprocessing step of the EEG signal analysis. Thus, it is possible to use topological analysis method for BCI systems, even though it is relatively slow when it is compared to band power based BCI systems.

TABLE I.

Subject No	**Kappa Values**			
	1-2	***1-3***	***2-3***	***1-2-3***
B01T	0.77	0.66	0.53	0.75
B02T	0.78	0.49	0.42	0.74
B03T	0.27	0.20	0.18	0.24
B04T	0.75	0.65	0.62	0.69
B05T	0.62	0.48	0.45	0.66
B06T	0.55	0.49	0.35	0.58
B07T	0.77	0.70	0.48	0.65
B09T	0.59	0.62	0.63	0.66

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