Classification of Multi-Class Motor Imaginary Tasks using Poincare Measurements Extracted from EEG Signals

EEG Sinyallerinden Çıkarılan Poincare Ölçümlerini Kullanarak Çok Sınıflı Motor Hayali Görevlerin Sınıflandırılması

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***Abstract*—Motor Imaginary (MI) electroencephalography (EEG) signals are generated with the recording of brain activities when a participant imagines a movement without physically performing it. The correct decoding of MI signals have been became an important task due to the application of these signals in the rehabilitation process of paralyzed patients in recent studies. However, the decoding of the these signals is still an evolving challenge in the design of a brain-computer interface (BCI) system. In this study, a machine learning based approach using Poincare measurements from non-linear measurements of MI EEG signals is proposed for classification of four-class MI tasks. The m-lagged Poincare plots were used to extract non-linear features and m is set to be values from 1 to 10. The performances of feature vectors which are extracted from 10 lag values and feature vector which is the combinations of these vectors were investigated separately in experimental evaluation section. The 24 different typical classification algorithms were tested in differentiating MI tasks using 5-fold cross-validation. Each of the these algorithms tested 10 times to analyzed the repeatability of the experimental results. The highest classifier performance of 47.08% among these 11 feature vectors was achieved over the combination feature vector that includes all lag values features using Quadratic Support Vector Machine (SVM). According to average accuracy value of 24 classifiers in 11 feature vector, the most discriminative feature set is 9th vector that consists of features extracted when lag value defined as 9. As a result, the innovative aspect of this study is the application of Poincare plots, one of the nonlinear feature extraction methods, in motor imaginary task classification.**

***Keywords*—brain-computer interface; EEG signals; machine learning; motor imaginary task classification; poincare plot**

***Özetçe*—Motor Hayali (MH) elektroensefalografi (EEG) sinyalleri, bir katılımcı fiziksel olarak gerçekleştirmeden bir hareketi hayal ettiğinde beyin aktivitelerinin kaydedilmesiyle üretilir. Son yıllarda yapılan çalışmalarda bu sinyallerin felçli hastaların rehabilitasyon sürecinde uygulanması nedeniyle MH EEG sinyallerinin doğru çözümlenmesi önemli bir görev haline gelmiştir. Bununla birlikte, bu sinyallerin kodunun çözülmesi, bir beyin-bilgisayar arayüzü (BBA) sisteminin tasarımında hala gelişen bir zorluktur. Bu çalışmada, dört sınıflı MH görevlerinin sınıflandırılması için MH EEG sinyallerinin doğrusal olmayan ölçümlerinden Poincare ölçümlerini kullanan makine öğrenmesi tabanlı bir yaklaşım önerilmiştir. M-gecikmeli Poincare grafikleri, doğrusal olmayan öznitelikleri çıkarmak için kullanıldı ve m, 1'den 10'a kadar olan değerler olacak şekilde ayarlandı. 10 gecikme değerinden elde edilen öznitelik vektörleri ile bu vektörlerin birleşimi olan öznitelik vektörünün performansları deneysel değerlendirme bölümünde ayrı ayrı incelenmiştir. 24 farklı tipik sınıflandırma algoritması, 5 kat çapraz doğrulama kullanılarak MI görevlerinin ayırt edilmesinde test edilmiştir. Bu algoritmaların her biri, deneysel sonuçların tekrarlanabilirliğini analiz etmek için 10 defa test edildi. Bu 11 öznitelik vektörü arasında 47,08% ile en yüksek sınıflandırıcı performansı, Kuadratik Destek Vektör Makinesi (DVM) kullanılarak tüm gecikme değerleri özniteliklerini içeren kombinasyon öznitelik vektörü üzerinden elde edilmiştir. 11 öznitelik vektöründe 24 sınıflandırıcının ortalama doğruluk değerine göre en ayırt edici öznitelik seti, gecikme değeri 9 olarak tanımlandığında çıkarılan özniteliklerden oluşan 9. vektördür. Sonuç olarak, bu çalışmanın yenilikçi yönü, doğrusal olmayan öznitelik çıkarma yöntemlerinden biri olan Poincare çizimlerinin motor hayali görev sınıflandırmasında uygulanmasıdır.**

Anahtar Kelimeler*—beyin-bilgisayar arayüzü; EEG sinyalleri; makine öğrenmesi; motor hayali görev sınıflandırması; poincare çizimi

I. INTRODUCTION

Brain-computer interface (BCI) sytems utilize brain signals generated based on different physiological processes such as slow cortical potentials, sensorimotor rhythms [1], P300 potentials [2], visual-evoked potentials (VEPs), and steady-state visual-evoked potentials (SSVEPs) [3]–[9] to supply control over the environment using a computer. One paradigm utilized in BCIs is the imagination of motor activity which generates variations on the power of electroencephalography (EEG) signals recorded over the motor cortex. The processing of the motor imaginary (MI) EEG signals plays an important role in the design of BCI systems due to the use of these signals in the rehabilitation process of paralyzed patients in recent studies [10]–[14]. However, the non-linear, non-stationary and low signal-to-noise ratio structure of EEG signals make the processing of these signals a difficult task. Therefore, effective signal processing methods have become an essential tool to differentiate MI tasks.

In last decades, traditional machine learning based approaches have been commonly used to classify MI EEG data. The processing of MI EEG signals in traditional methods consists of three main phase: preprocessing of signals, feature extraction, and classification [15]. The preprocessing phase includes some definite and significant processes of channel selection, signal filtering, signal normalization, and artifact removal. In traditional feature extraction processes, the hand-crafted features are extracted from MI EEG signals. The different types of features are generated based on domain information of signals which the signal is processed. These features were separated in three main groups based on their processing domain: temporal features, spectral features and spatial features. Temporal features are generated from time-domain utilizing time segments and time points of EEG signals such as mean value, skewness, kurtosis, variance, Hjorth parameters and root mean square value [15]. Spectral features categorized as frequency-domain based features which are power spectrum density (PSD) and Fast Fourier transform (FFT) [16], or time-frequency domain features which are Wavelet Transform (WT) [17] and short-time Fourier transform (STFT) [18]. In last decades, the most of the studies have been drawn on spatial-domain, the common spatial pattern (CSP) [19] and derivatives of it [20] were mainly used to extract spatial EEG features. In recent studies, it was observed that nonlinear measurements, which were effective in examining different physiological signals, have not been utilized to classify MI tasks. Poincare plot measurements are one of the non-linear measurements of physiological signals which is a popular technique due to its simple visual interpretation and its proved clinical ability as a predictor of disease and cardiac dysfunction [21]–[24]. The effect of Poincare plot measurements have not been analyzed to differentiate MI tasks. Considering its performance in other applications [25], [26], it can be an alternative method to the nonlinear structure that complicates the analysis of EEG signals in MI task classification.

In this study, a feature extraction method based on Poincare plot which is one of the non-linear measure technique and machine learning algorithms is proposed the differentiate MI tasks. The experimental process were conducted on 22-channel MI EEG signals for four-class MI task classification.

II. MATERIALS & METHODS

A. Dataset

The publicly available an international BCI Competition IV Dataset-IIa were used to test the proposed method [28]. BCI Competition IV Dataset-IIa includes 22 EEG signals of 9 participants (4 female and 5 male). The experiment is designed as cue-based BCI paradigm including four different motor imagery tasks which are the imagination of movement of the left hand (class 1), right hand (class 2), both feet (class 3), and tongue (class 4). EEG signals were collected as two sessions on different days. 6 runs are available in each sessions and runs were extracted with short breaks. Each runs include 48 trials in total, with 12 trials for each class. The experimental process yields a total of 288 trials for per subject. In EEG data recording, twenty-two Ag/AgCl electrodes were utilized. The sampling with 250 Hz and bandpass-filter between 0.5 Hz and 100 Hz processes were applied to EEG signals in preprocessing section. And, the line noise was eliminated using application of 50 Hz notch filter. EEG segments where MI tasks are performed were separated from signals in preprocessing of this study.

B. Poincare Plot Measures

Poincare plot measurements are known as an one of the non-linear measurements of EEG signals that used to represent the nonlinear dynamics inherent in the signal. It is a drawing where each EEG (x_i) data is placed on the x-axis and the following (x_{i+lag}) interval is placed on the y-axis [21]. Poincare plot was used to extract features in analysis of different type of biomedical signals due to its simple visual interpretation and proved clinical ability [21]–[24]. The effect of the Poincare plot-based feature extraction process for MI EEG signal classification was investigated in the proposed study based on the positive aspects in the literature. Poincare drawings were created using raw MI EEG signals. An ellipse is fitted the Poincare plot's scheme and the standard deviation of the points on the plot denotes the width of the ellipse (SD_1) and the length of the ellipse (SD_2) [21].

The Poincare plot measures are mathematically computed using the following equations. The two interval vector represented in Equations (1)–(2) and the measurements of SD_1 and SD_2 were calculated using Equations (3)–(4) based on these intervals. Then, the four different Poincare plot measurements were calculated in the feature extraction process [21]:

$$x_i = (x_0, x_1, ..., X_{N-m}) \quad (1)$$

$$x_{i+lag} = (x_m, x_{m+1}, ..., X_N) \quad (2)$$

$$x_a = \frac{x_{i+lag} - x_i}{\sqrt{2}}$$

$$x_b = \frac{x_{i+lag} + x_i}{\sqrt{2}} \quad (3)$$

Models	**lag=1**	**lag=2**	**lag=3**	**lag=4**	**lag=5**	**lag=6**	**lag=7**	**lag=8**	**lag=9**	**lag=10**	**all lags**
Fine Tree	29.10	30.10	29.60	29.30	29.40	30.60	30.50	31.40	31.30	31.10	**31.90**
Medium Tree	28.80	28.40	29.60	29.30	28.30	28.20	29.00	30.70	**31.50**	30.80	30.20
Coarse Tree	28.00	27.50	27.00	28.90	28.10	27.50	28.70	27.90	28.40	**29.40**	27.90
Linear Discriminant Analysis	40.00	40.50	40.00	41.70	40.10	41.90	**42.70**	42.30	**42.70**	41.70	40.20
Quadratic Discriminant	35.70	36.50	37.40	**39.20**	37.20	37.70	35.80	36.60	36.30	36.10	Failed
Gaussian Naive Bayes	26.80	27.40	27.90	28.30	27.90	**29.00**	28.00	28.00	28.90	28.40	28.30
Kernel Naive Bayes	26.80	28.30	27.90	28.60	28.00	28.50	27.90	28.20	**30.00**	27.90	28.20
Linear Support Vector Machine	37.17	38.97	39.06	39.96	39.92	40.56	40.95	41.51	41.86	40.71	**42.96**
Quadratic Support Vector Machine	41.01	43.16	44.30	44.51	42.98	43.07	44.36	44.48	43.41	43.78	**47.08**
Cubic Support Vector Machine	39.07	40.50	41.57	40.33	41.21	41.62	41.77	42.38	42.14	41.24	**44.47**
Fine Gaussian Support Vector Machine	31.40	31.80	33.90	**34.70**	33.20	32.80	**34.70**	34.10	34.60	34.60	33.50
Medium Gaussian Support Vector Machine	30.60	32.10	33.90	35.10	34.10	36.10	35.60	36.10	**38.00**	36.60	35.90
Coarse Gaussian Support Vector Machine	28.90	28.50	28.20	29.60	29.60	30.50	31.00	30.90	**32.20**	30.80	29.30
Fine K-Nearest Neighbours	30.70	29.90	29.10	31.40	31.40	29.90	**32.00**	31.20	30.80	31.30	30.60
Medium K-Nearest Neighbours	30.80	29.40	30.30	30.90	30.20	30.40	29.90	**31.50**	31.40	**31.50**	30.00
Coarse K-Nearest Neighbours	29.70	29.80	31.20	32.40	29.90	30.70	31.40	32.30	**33.00**	31.40	30.60
Cosine K-Nearest Neighbours	32.20	32.10	32.50	31.90	32.10	32.40	32.20	**33.30**	33.10	32.30	32.30
Cubic K-Nearest Neighbours	29.80	29.20	30.50	30.40	30.50	31.10	30.90	31.00	31.90	**32.60**	31.90
Weighted K-Nearest Neighbours	29.90	29.90	30.40	31.30	31.10	30.40	30.50	31.40	32.30	**33.00**	31.40
Ensemble Boosted Trees	30.10	28.50	30.00	31.70	29.00	28.80	29.30	32.10	32.60	31.30	**32.80**
Ensemble Bagged Trees	32.18	32.84	33.16	32.70	32.20	32.96	33.37	33.00	34.12	34.00	**34.18**
Ensemble Subspace Discriminant	39.59	41.20	41.53	42.08	40.19	42.17	42.84	42.94	43.42	42.27	**46.06**
Ensemble Subspace K-Nearest Neighbours	28.14	30.88	29.98	31.05	31.28	**31.40**	30.60	29.93	30.67	29.32	29.70
Ensemble RUSBoosted Trees	28.74	28.64	27.90	31.10	28.24	28.31	28.78	30.84	**31.70**	31.23	30.31
Average	31.88	32.38	32.72	33.65	32.76	33.19	33.45	33.92	**34.43**	33.89	33.91

Table I: Multi-class motor imaginary task classification results of feature vectors extracted from each lag values based on average accuracy values (%) of 10 tests.

$$SD_1 = SD(x_a)$$
$$SD_2 = SD(x_b) \tag{4}$$

SD denoted the standard deviation of the extracted time interval vectors. The different intervals created using m-lagged Poincare plot measurements for this study. The measurements of SD_1 and SD_2 were calculated for lag=m. In the study, set m from 1 to 10. In addition to measurements of SD_1 and SD_2 , the product ($SD_1 SD_2$) and the ratio (SD_1/SD_2) were calculated to examine the relationships between these components.

As a result, the four different Poincare plot measures were extracted for each EEG channels and total of 88 feature obtained for each EEG signal. 288x88 (number of trials x number of features) feature vector was obtained for each subject. Then, 2592x88 feature vector was created from 9 subjects for each lag value.

C. Classification

The 11 feature vectors were obtained from MI EEG signals. 10 of these feature vectors were created for each 10 lag value separately and the last vector consists of combination of these 10 lag feature vectors. The classification process conducted on each feature vector separately. Train and test data groups were created splitting feature vectors based on 5-fold cross-validation. The performances of each feature vector evaluated with various machine learning algorithms. The multi-class (right hand, left hand, feet, and tongue) MI tasks classification process computed drawing on 24 different classifier algorithms which are commonly used in the literature [27]. The repeatability of the classification results examined testing each classification algorithms 10 times. Performance evaluations were carried out based on true positives (TP), (true negatives) TN, false positives (FP) and false negatives (FN) values which were obtained from confusion matrices. The performance metrics of accuracy, specificity and sensitivity were calculated to investigate performance of different tests. The calculation of these metrics computed using following equations:

$$Accuracy(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{5}$$
$$Sensitivity(\%) = \frac{TP}{TP+FN} \times 100 \tag{6}$$
$$Specificity(\%) = \frac{TN}{TN+FP} \times 100 \tag{7}$$

III. Experimental Results

In this study, a machine learning based approach using Poincare plot measures was introduced to classify four different MI tasks. The feature extraction and classification processes in the study were carried out in MATLAB application. The m-lagged Poincare plot measurements were computed and m set from 1 to 10 for feature extraction process. Poincare plot measurements generated the four different non-linear features from EEG signals. A feature vectors were extracted from each of 10 lag values and the combination of these vectors that includes all lag features was created. A total of 11 feature vectors were created in the feature extraction phase. These vectors were evaluated separately to investigate the effects of the different lag values and combination of them. These vectors were classified with 24 different classification algorithm

Study	Dataset	Number of Channels	Feature extraction	Feature selection	Classes	Classifier	ACC (%)	SEN (%)	SPE (%)
[15]	BCI Competition IV Dataset-IIa	22 EEG	Time-domain features	ANOVA	Left hand, Right hand, Feet, Tongue	Linear Discriminant Analysis	44.00	44.30	44.31
[29]	MISCP	21 EEG	Multi-class CSP	N/A	Five fingers	SVM	40.60	N/A	N/A
[30]	BCI Competition IV Dataset-IIa	8 EEG	FFT, Channel Variance	Principal Component Analysis	Left hand, Right hand, Feet, Tongue	Least Squares SVM	56.00	N/A	N/A
[31]	BCI Competition IV Dataset-IIa	22 EEG	CSP	N/A	Left hand, Right hand, Feet, Tongue	Fuzzy Logic System	65.00	N/A	N/A
This study	BCI Competition IV Dataset-IIa	22 EEG	Poincare plot measures	N/A	Left hand, Right hand, Feet, Tongue	Quadratic SVM	47.08	47.13	47.15

Table II: Comparison of multi-class motor imaginary task classification studies with the results of the proposed study. ACC, SEN, and SPE are the accuracy, sensitivity, and specificity, respectively.

based 5-fold cross-validation technique. Each classification algorithms tested 10 times and average accuracy values of these tests were calculated. The average accuracy values of 10 tests were evaluated for 24 different classification algorithms over 11 feature vectors and experimental results are given in the Table I. Experimental results represented that the maximum average accuracy value of 47.08% achieved using Quadratic Support Vector Machine (SVM) classifier over 11th feature vector that includes the features of all lags.

IV. Discussion and Conclusion

The aim of this study is to investigate the effects of the non-linear features on multi-task classification. The Poincare measurements were used to extract non-linear features based on 10 different lag values. The effect of 11 different feature vectors on classifiers performance was investigated separately. In Table I, the performance effect of lag values on 24 different classifiers is given based on the average accuracy values. The results in Table I demonstrated that the maximum average accuracy values were obtained in 2 classifiers from lag=4 feature vector, 2 classifiers from lag=6 feature vector, 3 classifiers from lag=7 feature vector, 2 classifiers from lag=8 feature vector, 7 classifiers from lag=9 feature vector, 4 classifiers from lag=10 feature vector, 7 classifiers from feature vector including all lag features. In this study, the maximum classification performance was calculated to be 47.08% with the combination vector of the extracted features using 10 lag values. Although the maximum classification success was achieved in the combination vector, it was observed that the maximum classification accuracy value was achieved in the vectors obtained from only a single lag value in 20 classifiers in the tests computed on 11 feature vectors. When the results are examined, the most effective and successful feature vector among the vectors obtained from a single lag value consists of the features extracted by determining the lag value as 9. Also, the average accuracy values of 24 different classifiers were calculated for each of the 11 feature vectors and the maximum average accuracy was calculated as 34.43% over feature vector consists of lag=9 features.

This study is compared with machine learning studies that performed multi-class motor imaginary task classification and the results with detail information about studies are given in Table II. It has been observed that classification performances are achieved at lower rates in multi-task classification than in binary classification especially for machine learning based studies. In [30], channel reduction process was computed and 8 EEG channel was used to extract features. Also, the different combinations of feature extraction methods with effective feature selection methods was tested to obtain highest accuracy value. Based on the results of these studies, it has been concluded that the performances of the proposed study can be improved in further studies by determining the effective channels and using effective feature selection methods.

The main contributions of the proposed study can be highlighted as follows:

- We propose a non-linear feature extraction method computing Poincare plot measurements of EEG signals to classify multi-class MI task classification.
- We investigate the performance effect of the different 10 lag values separately.
- The multi-directional analyzes are performed in which 24 different classifier algorithms are tested on 11 different feature vectors.

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