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NORMALIZED ITAKURA DISTANCE BASED DISCRIMINATION USED IN A MOTOR IMAGERY BRAIN COMPUTER INTERFACE PARADIGM

BY

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Abstract. Detection and classification of changes that appear in electroencephalogram (EEG) during mental tasks are investigated. Based on the autoregressive modelling, the normalized Itakura distance (nID) is used to quantify the changes reflected in the EEG signals. A database with 9 subjects is investigated. Statistical tests are performed in order to extract the relevant EEG channels. The classification is performed using linear discriminant classifier (LDA), quadratic discriminant classifier (QDA), Mahalanobis distance classifier (MD), k nearest neighbor (kNN) and support vector machine (SVM). The results suggest that normalized Itakura distance can be used as an offline method for motor imagery paradigms.

Key words: brain computer interface (BCI); electroencephalogram (EEG); motor imagery; Mu rhythm; normalized Itakura distance (nID).

1. Introduction

People with severe motor disabilities require alternative methods for communication and control. Electroencephalogram (EEG) based communication systems measure specific features of brain activity and use the

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results as control signals (McFarland *et al.*, 2009). These systems are relatively inexpensive; they have a simple procedure of acquiring EEG signals and good temporal resolution of them.

The motor imagery paradigm is one of the main EEG based brain computer interface systems. By thinking about moving their limbs, the subjects can produce relevant patterns, named event-related (de)synchronization (ERD/ERS) in Mu (8,...,12 Hz) or Beta (12,...,30 Hz) rhythms of the EEG signals (Pfurtscheller *et al.*, 1999).

The cortical areas involved in motor function show activity when the person performs motor imagery tasks. When the person is engaged in a motor task the neural networks in the corresponding cortical areas are activated. This blocks the idle synchronized firing of the neurons and thus it causes a measurable attenuation in the frequency range of 8,...,12 Hz or 8,...,30 Hz. The location of this feature depends on the type of motor task. For example, if a person moves his left arm, the contralateral brain region will display this ERD feature, while the neurons in the ipsilateral cortical motor area continue to fire synchronously (Devlaminck *et al.*, 2009).

Different methods for detection and classification of ERD/ERS due motor imagery were proposed during last years. The Mahalanobis distance is examined in (Babiloni *et al.*, 2001), a two-equivalent dipole model for source analysis it is proposed in (Kamousi *et al.*, 2005) and the Hurst exponent is estimated using different types of wavelet in (Aldea *et al.*, 2013).

In this paper we proposed a method based on normalized Itakura distance to discriminate between mental tasks (left and right hand imagination) in a motor imagery BCI paradigm.

2. Methodology

2.1. Data Collection

The database from BCI competition 2002 provided by dr. Osman is used (Osman *et al.*, 2001). The EEGs were recorded from 9 well trained subjects who were asked to imagine left or right hand movement. Each subject had to perform 180 trials (90 left hand movement imaginations, 90 right hand movement imaginations). The timing of the experiment is shown in Fig. 1 and each trial epoch lasted 6 s. The EEG signals were recorded with 59 electrodes placed on the scalp according to International 10/20 system and the reference was on the left mastoid. The sampling frequency is 100 Hz.

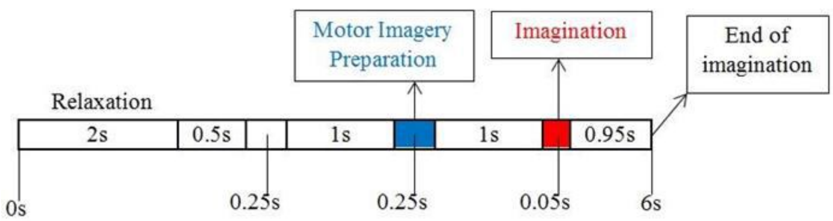

Fig. 1 – The experimental paradigm.

As Mu rhythm desynchronizations appear in the motor cortex, only 12 electrodes (FC3, FC1, FC2 ,FC4 ,C3 ,C1, C2, C4, CP3, CP1, CP2, CP4) are selected for further processing (Wolpaw *et.al*, 2002).

2.2. The Autoregressive Model

The autoregressive model (AR) is used to characterize EEG signals and to quantify the changes that appear during mental tasks.

The two most popular and well-established methods for AR parameter estimation are the autocorrelation method, in which the Yule-Walker equations are solved using the Levinson-Durbin algorithm, and the maximum entropy method, as implemented by the Burg algorithm (Pardey *et. al*, 1996).

The EEG signal, $y(n)$, is assumed to be the output of an autoregressive system driven by white noise.

The AR model is represented by:

$$y(n) = -\sum_{k=1}^{p} a_k y(n-k) + e(n), \tag{1}$$

where: a_k are the parameters of the model, p – the model order and $e(n)$ – the prediction error.

2.3. The Itakura Distance

The Itakura Distance (ID) was mainly used to measure the similarities between voice signals (Itakura, 1975) and to separate sleep stages (Estrada, 2004).

We denoted the relaxation EEG signal by $y_{\text{RELAX}}(n)$, the EEG signal corresponding to the imagination of the left hand by $y_{\text{LEFT}}(n)$, the EEG signal corresponding to the imagination of the right hand by $y_{\text{RIGHT}}(n)$ and the model order p (the same for all AR processes). The parameters a_k^{RELAX}, a_k^{LEFT}, a_k^{RIGHT}, $k = 1,2,3,\ldots, p$ characterizing the processes are:

$$a^{\text{RELAX}} = \begin{bmatrix} 1 & a_1^{\text{RELAX}} & a_2^{\text{RELAX}} & \ldots & a_p^{\text{RELAX}} \end{bmatrix}^T, \tag{2}$$

$$a^{\text{LEFT}} = \begin{bmatrix} 1 & a_1^{\text{LEFT}} & a_2^{\text{LEFT}} & \ldots & a_p^{\text{LEFT}} \end{bmatrix}^T, \tag{3}$$

$$a^{\text{RIGHT}} = \begin{bmatrix} 1 & a_1^{\text{RIGHT}} & a_2^{\text{RIGHT}} & \ldots & a_p^{\text{RIGHT}} \end{bmatrix}^T. \tag{4}$$

When $y_{\text{RELAX}}(n)$ represents the output of the AR(p) model for the relaxation period, the minimum square error (MSE) is:

$$\text{MSE}_{y_{\text{RELAX}} y_{\text{RELAX}}} = \left(a^{\text{RELAX}}\right)^T R_{y_{\text{RELAX}}}(p) a^{\text{RELAX}}, \tag{5}$$

where: $R_{y_{\text{RELAX}}}(p)$ is the autocorrelation matrix for $y_{\text{RELAX}}(n)$, (Kong *et* al., 1995).

The MSEs when the relaxation EEG signal is the output of any other AR(p) model, described by a^{LEFT} or a^{RIGHT} parameters are:

$$\text{MSE}_{y_{\text{RELAX}}y_{\text{LEFT}}} = \left(a^{\text{LEFT}}\right)^T R_{y_{\text{RELAX}}}(p)a^{\text{LEFT}}, \tag{6}$$

$$\text{MSE}_{y_{\text{RELAX}}y_{\text{RIGHT}}} = \left(a^{\text{RIGHT}}\right)^T R_{y_{\text{RELAX}}}(p)a^{\text{RIGHT}}. \tag{7}$$

The IDs between the relaxation state and left/ right motor imagery state are as follows:

$$\text{ID}_{\text{RELAX-LEFT}} = \log\left(\frac{\text{MSE}_{y_{\text{RELAX}}y_{\text{LEFT}}}}{\text{MSE}_{y_{\text{RELAX}}y_{\text{RELAX}}}}\right), \tag{8}$$

$$\text{ID}_{\text{RELAX-RIGHT}} = \log\left(\frac{\text{MSE}_{y_{\text{RELAX}}y_{\text{RIGHT}}}}{\text{MSE}_{y_{\text{RELAX}}y_{\text{RELAX}}}}\right). \tag{9}$$

A normalization procedure 0-100 is performed and it is defined by:

$$\text{NORM}_{\text{ID}_{\text{RELAX-LEFT}}} = \frac{\left[\text{ID}_{\text{RELAX-LEFT}} - \min\left(\text{ID}_{\text{RELAX-LEFT}}\right)\right]\times 100}{\max\left(\text{ID}_{\text{RELAX-LEFT}}\right) - \min\left(\text{ID}_{\text{RELAX-LEFT}}\right)}, \tag{10}$$

$$\text{NORM}_{\text{ID}_{\text{RELAX-RIGHT}}} = \frac{\left[\text{ID}_{\text{RELAX-RIGHT}} - \min\left(\text{ID}_{\text{RELAX-RIGHT}}\right)\right]\times 100}{\max\left(\text{ID}_{\text{RELAX-RIGHT}}\right) - \min\left(\text{ID}_{\text{RELAX-RIGHT}}\right)}. \tag{11}$$

The block diagram of the proposed method, based on normalized Itakura distance, is illustrated in Fig. 2.

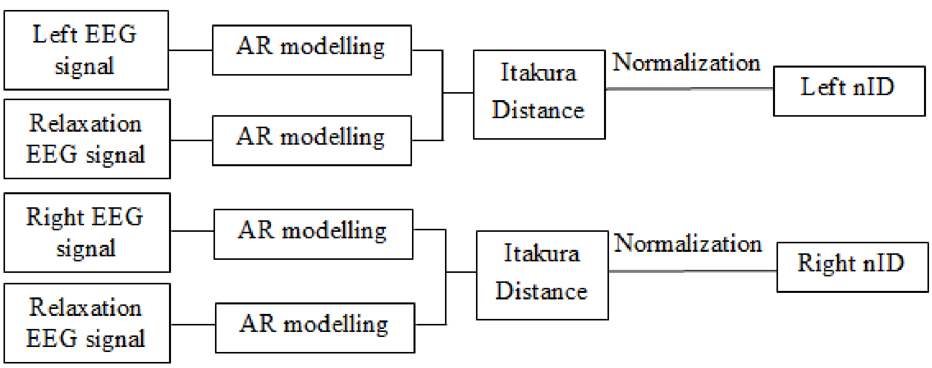

Fig. 2 – The proposed method based on normalized Itakura distance.

3. Results

Sequences of the EEG segments are extracted for each mental task. Four sets of data are formed: the right motor imagery, the relaxation succeeding right motor imagery, the left motor imagery, the relaxation succeeding left motor imagery.

The method is applied on Mu rhythm (frequency range 8,…,12 Hz). Model orders p = 6 and p = 10 are selected for AR processes as indicated in Kong *et al.* (1995) and Estrada *et al.* (2005).

The normalization of the ID is performed for all trials, all selected channels and for all subjects.

The statistical difference between right nID and left nID is evaluated. Shapiro-Wilk test (King *et al.*, 2012) is performed in order to see if nIDs follow a normal distribution. If data have a normal distribution, paired t-test is applied for assessing left and right ID statistical difference. On channels that have not met the normality condition, Wilconox signed-rank test is performed.

The selected channels after applying the statistical tests for model order 6 and 10 and for each subject are shown in Table 1.

Table 1
The Selected Channels for Fixed Model Orders for Each Subject

	Subjects								
Model order	**Subject 1**	**Subject 2**	**Subject 3**	**Subject 4**	**Subject 5**	**Subject 6**	**Subject 7**	**Subject 8**	**Subject 9**
6	C2 CP1 CP2	FC1 CP4	C3 CP3 CP2 FC3 FC4 C1 CP1 CP4	–	FC3 FC1 FC2 FC4 C1 C4 CP2	–	CP1	CP4 FC4 C3 C1 CP3 CP1	FC2 C2 C4 FC3 FC1 CP1 CP4
10	C2 CP4 FC3 CP1 CP2	C4 FC1	CP3 CP2	FC2 C1 CP2 C3 C4	C4 FC3 FC1 FC2 C1 C2 CP4	FC1 C4	C3 C4	FC1 FC2 CP2 FC4 C3 C1 C2 C4 CP3	C2 C4 FC3 FC1 CP1

For model order 6, subjects 4 and 6, are excluded for further processing, because no channel fulfilled the imposed conditions by statistical tests. For subject 3, from 12 channels, 8 channels are selected, while for subject 7 only channel CP1 is chosen.

Regarding the model order 10, for subject 8 a number of 9 channels are chosen. Only 2 channels are selected during statistical test for subjects 2, 3, 6 and 7.

A 10 × 10 fold cross validation estimated the classification rate for each subject. The used classifiers are: linear discriminant analysis (LDA) (Garrett *et al.*, 2003), quadratic discriminant analysis (QDA) (Hastie *et al.*, 2005), Mahalanobis distance (MD) (Babiloni *et al.*, 2001), *k* nearest neighbor (KNN) (Chaovalitwongse *et al*., 2007) and support vector machine (SVM) (Bennett *et al.*, 2000).

LDA is one of the most popular classification algorithms for motor imagery based BCI, P300 speller and steady state visual evoked potentials based BCI. QDA is closely related to LDA. Although it is not reported and used as much as linear classifier in BCI systems, the quadratic classifier reported satisfactory and encouraging results. MD is a statistical distance function. Despite its good performance, it is still rarely used in the literature on BCI. KNN is not very popular in the BCI community. However, when used in BCI systems with low-dimensional feature vectors, kNN may prove to be efficient. SVM uses a discriminant hyperplane to identify classes and provides good results in BCI applications due its advantages: good generalization properties, insensitive to overtraining and low speed of execution (Lotte *et al*., 2007).

Figs. 3 and 4 display the classification rates obtained with LDA, QDA and MD classifiers for model order 6 and 10.

For model order 6 the highest classification rates are achieved with LDA (above 60%). Subject 5 had the highest rates, while subject 7 the smallest ones.

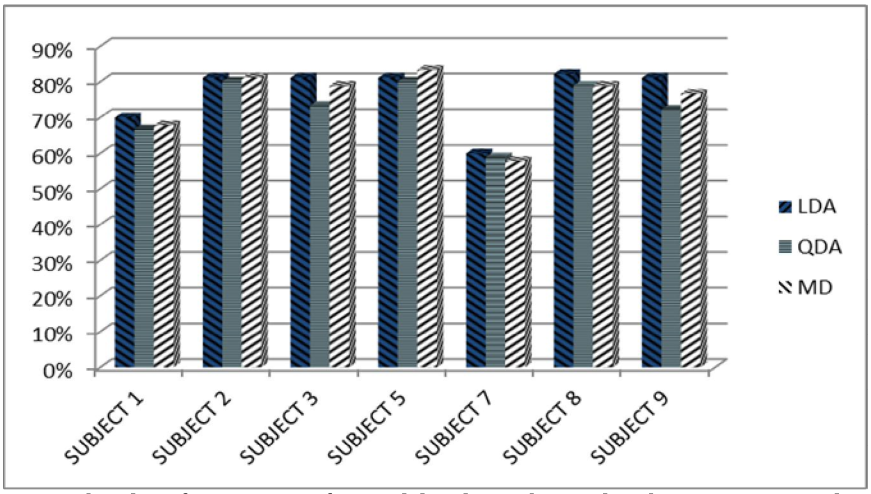

Fig. 3 – The classification rates for model order 6 obtained with LDA, QDA and MD classifiers.

The classification rates obtained with model order 10 are in the range 59,…,91%. The smallest discrimination rate is obtained with quadratic classifier (59% – subject 6) and the highest discrimination rate with linear classifier (91% – subject 4).

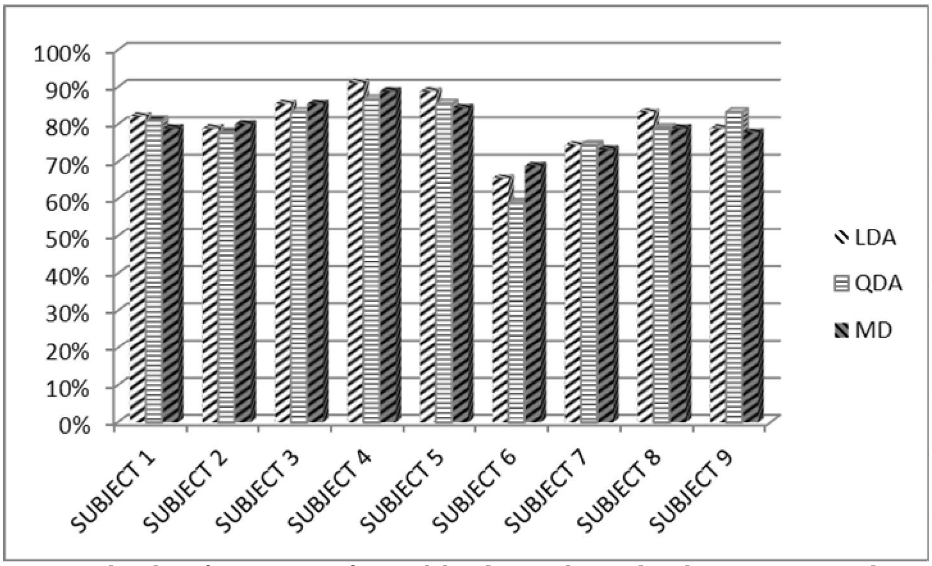

Fig. 4 – The classification rates for model order 10 obtained with LDA, QDA and MD classifiers.

Table 2 presents the classification rates obtained with KNN classifier based on the outcome of the *k* (1, 2, 3, 4 and 5) neighbors for model order 6. The highest discrimination rates are achieved with a number of 5 neighbors for subjects 1, 3, 5, 9.

Table 2
The Classification Rates for Model Order 6 Obtained with KNN

Subjects	Number of neighbors				
	1	2	3	4	5
1	63.53%	63.59%	63.66%	63.95%	64.00%
2	81.34%	80.99%	81.11%	81.00%	80.67%
3	80.73%	81.19%	81.40%	81.82%	82.22%
5	80.98%	81.43%	81.86%	82.27%	82.67%
7	55.61%	55.95%	55.58%	55.68%	55.33%
8	76.32%	76.29%	76.27%	76.24%	76.22%
9	80.73%	80.71%	80.93%	81.14%	81.33%

Table 3 is similar to Table 2, but for model order 10. The smallest classification rate is 60.63% – subject 6 for one neighbor, but only 2 channels are selected for processing. For subject number 8, where 9 channels are selected, the classification rates are in the range 81.71%,…,82.44%. Excepting subjects 6 and 7, the other subjects achieved discrimination rates above 74%. The best classification rates belong to subject 9, range 81.88%,…,82.44%.

Table 3
The Classification Rates for Model Order 10 Obtained with KNN

Subjects	Number of neighbors				
	1	2	3	4	5
1	76.09%	76.36%	76.62%	76.87%	76.89%
2	74.88%	74.94%	74.54%	74.15%	73.78%
3	75.60%	75.89%	76.16%	76.42%	76.44%
4	76.33%	75.65%	75.23%	74.38%	74.22%
5	87.80%	87.62%	87.44%	87.27%	87.11%
6	60.63%	60.99%	61.34%	61.68%	61.78%
7	65.94%	65.25%	64.81%	64.17%	63.78%
8	81.64%	81.32%	81.71%	82.09%	82.44%
9	81.88%	82.03%	82.18%	82.31%	82.44%

Table 4 shows the comparison between classification rates attained with SVM classifier, for model orders 6 and 10. It is important to notice that, for 90% of subjects, the classification rates obtained with model order 10 are higher than those acquired with model order 6.

Table 4
The Classification Rates for Fixed Model Orders Obtained with SVM Classifier

Subjects	Model order	
	6	10
1	60.00%	84.44%
2	80.00%	77.78%
3	77.78%	88.89%
4	–	75.56%
5	84.44%	80.00%
6	–	46.67%
7	57.78%	71.11%
8	75.56%	75.56%
9	84.44%	80.00%

Overall the highest classification rates were obtained with kNN classifier.

The findings are consistent with other works (Ince *et al.*, 2007; Kamousi *et al*., 2005) in which the dataset exploited by this paper is used. So, in (Ince et al., 2007) where is investigated a time–frequency approach using six subjects (1, 2, 5, 6, 7, 9), for subject 2 and subject 5 are reported the classification rates 91.4% and 76.1% respectively. With normalized Itakura distance, for subject 2 the classification rates achieved were in the range 71.11%,…,81.34%, while for subject 5 the classification rates were above 80.00%.

4. Conclusions and Future Research

Based on autoregressive modeling, the proposed method explores the normalized Itakura distance for a motor imagery paradigm. Statistical tests discarded the irrelevant information and maintained in the study only the channels with important features which were used in classification. Based on achieved classification rates, we can conclude that normalized Itakura distance can detect changes that appear during mental tasks, it is simple to apply and it can be used as an offline method for BCI paradigms.

Further work implies developing and testing generalized Itakura distance and using combinations of classification methods for improving the classification rates.

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DISCRIMINAREA PE BAZA DISTANȚEI ITAKURA NORMALIZATE UTILIZATĂ ÎNTR-O PARADIGMĂ DE IMAGINARE MOTORIE FOLOSIND INTERFAȚA CREIER CALCULATOR

(Rezumat)

Se investighează detectarea şi clasificarea modificărilor care apar în electroencefalogramă (EEG) în timpul sarcinilor mentale. Bazată pe modelul autoregresiv, distanța Itakura normalizată (nID) este utilizată pentru a cuantifica modificările reflectate în semnalele EEG. În acest studiu este folosită o bază de date cu 9 subiecți. Testele statistice au fost efectuate pentru de a extrage canalele EEG relevante. Clasificarea se realizează cu ajutorul analizei discriminante liniare (LDA), a analizei discriminante pătratice (QDA), a clasificatorului bazat pe calcularea distanței Mahalanobis (MD), a algoritmului celui mai apropiat vecin k (kNN) şi a clasificatorului vector suport (SVM). Rezultatele obținute sugerează că distanța Itakura normalizată poate fi folosită ca o metodă de analiză offline pentru paradigmele bazate pe imaginarea motorie în interfețele creier-calculator.