AUTOMATIC SELECTION OF CLASSIFIERS FOR GAIT PLANNING RECOGNITION THROUGH A BCI

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Abstract—A new method is introduced here to automatically search a suitable setup of classifiers for a brain computer-interface (BCI), in order to improve the gait planning recognition. The method uses statistical analysis based on bootstrap confidence interval, density distribution and ranking, through the mean and median values, obtained from the training stage with several inner cross-validation. The method was evaluated on five subjects, using a BCI based on Linear Discriminant Analysis (LDA) with three possible setups: diagonal, full, or spherical covariance matrix. The proposed method selected the diagonal and full covariance matrices, with the diagonal covariance matrix presenting the highest values of accuracy (ACC), true positive rate (TPR), and false positive rate (FPR) of 78%, 89% and 27%, respectively. For almost all subjects, values of ACC higher than 70% were obtained, as well as values of TPR and FPR between 54-59 %, and 18-30%, respectively. This approach could be used to obtain an unsupervised BCI, which may be used to improve the training step during gait planning and recognition.

Keywords—BCI, LDA, feature selection, gait planning, pattern recognition, unsupervised method

1 Introduction

A brain-computer interface (BCI) can provide for people with severe motor disabilities a direct control on robotic exoskeletons, using patterns related to motor intention, such as slow cortical potentials (SCPs) and event-related desynchronization/synchronization (ERD/ERS) (Hashimoto and Ushiba, 2013; Xu et al., 2014; Jiang et al., 2015; Hortal et al., 2016). Several works have used the anticipation information (from ~2.0 s before movement) from EEG (Xu et al., 2014; Jiang et al., 2015; Sburlea et al., 2015; Sburlea, Montesano and Minguez, 2016), in order to obtain more natural onset movements and improve the neural injury repair. In addition, BCI works have been applied using motor pattern recognition to provide a direct control on the device (Xu et al., 2014; Hortal et al., 2016).

Motor anticipation recognition is a challenge, due to the pattern uncertain related to intra-subject reaction time variability, EEG variability, and other unknown criteria, such as event duration, among others. Nowadays, several BCI use supervised methods to recognize motor planning (Garrett et al., 2003; Hashimoto and Ushiba, 2013; Hortal et al., 2016), where the performance may be affected by patterns selected in the learning stage. For instance, many works have employed genetic algorithms based on classifiers for dimensionality reduction, in order to improve the BCI speed (Garrett et al., 2003). These methods provide a feature set highly correlated to the classifier complexity, with high computational cost. Furthermore, regularized classifiers as Support Vector Machine (SVM) and k-Nearest Neighbor (KNN) could be of little use for this stage, for processing clusters with high uncertainty, as well as unknown spatial distribution.

On the other hand, many authors have shown a good performance during motor intention recognition, using classifiers such as Linear Discriminant Analysis (LDA), Regularized Discriminant Analysis (RDA), and SVM with kernels linear and Radial Basic Function (RBF) (Lotte et al., 2007). However, the performance of these classifiers may be affected according to the setup adopted on each subject. This way, some authors have explored the LDA classifier with different setups based on the covariance matrix (diagonal, spherical, full, among others), in order to improve the BCI performance (Vidauur and Blankertz, 2010; Vidauur et al., 2011). As a result, full covariance has shown better performance than the diagonal matrix, during motor intention recognition. Other authors have demonstrated that RDA with spherical covariance matrix may be used to recognize gait intention (Velu and de Sa, 2013). In addition, SVM with kernel linear or RBF has shown a good performance in applications of motor intention recognition, specifically gait planning. However, little works have presented the optimized setup of these classifiers, as well as the methodology used to fit the classifier.

The objective of this work is to propose an automatic method to search a suitable setup for some classifiers during the training stage, in order to improve the gait planning recognition in a BCI. The proposed
method was evaluated in a BCI using LDA, to recognize gait planning, using three covariance matrices as setup.

2 Approach

Figure 1 shows the block diagram of the proposed method to search automatically a suitable model of classification during the training stage in a BCI, in order to improve the gait planning recognition. The training set used at the classification stage to obtain the performance of several setups during an inner cross-validation k-fold (k = 40). Some well-known parameters such as true positive rate (TPR), false positive rate (FPR), Kappa, accuracy (ACC), and PNM were combined to obtain a unique index $\text{Idx}$ (see Eq. 2) using weighted indices, in order to analyze the performance of each setup throughout all k-fold.

PNM measures the combined misclassification in the prediction of each class (resting from stand position, and gait planning) (Castro, Arjunan and Kumar, 2015), and can be computed by the following equation:

$$PNM_i = \frac{\sum_{j=1}^{K} C_{ij} - \sum_{j=1}^{K} \sum_{i' \neq i}^{K} C_{i'j}}{\sum_{j=1}^{K} C_{ij} + \sum_{i' \neq i}^{K} C_{i'j}},$$  \hspace{1cm} (1)

where $C_{ij}$ is an element of the confusion matrix that corresponds to the row $i$ and column $j$, and $K$ is the total number of classes. PNM takes values from 1, if all predictions are correct, to -1 if all predictions are wrong. Thus, the index $\text{Idx}$ is given by:

$$\text{Idx} = 1 - \sum_{i=1}^{n} w_i p_i,$$  \hspace{1cm} (2)

where $w_i$ is the index weighted assigned to the parameter $i$, $w = [0.3, 0.3, 0.15, 0.25]$, and $P = [\text{Kappa}, (1-FPR_{\max}), \text{ACC}, \text{PNM}_{\min}]$.

After finishing the k-fold process, a statistical evaluation is carried out through the bootstrap confidence interval and density distribution analysis. The bootstrap confidence analysis was applied on the mean and median values throughout 2000 iterations, using the normal criteria. Afterwards, the outputs of the bootstrap samples are analyzed from the density distribution to compute the expected values for the mean and median. Finally, a ranking analysis is performed on all setups, using the mean and the upper value of the confidence interval, respect to the mean and median values related to classification outputs.

3 Materials and Methods

2.1 Protocol

Five healthy subjects (31.8 ± 5.98 years old) without lower limb injury or locomotion deficits were selected to participate in this study (Protocol number: 47024214.5.0000.5060), which was approved by the Ethics Committee of UFES (Brazil). EEG electrodes were located on FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6 and Pz, according to the international 10-20 system. BrainNet BNT 36 was the equipment used to measure EEG signals, using a band-pass filter from 0.1 to 100 Hz, a notch filter at 60 Hz, and sampling rate of 400 Hz. The reference electrodes were located on earlobes A1 and A2, and the ground electrode was located between the eyebrows. The acquisition system was attached to a mobile platform in order to follow the subjects during walking. The subjects were cued through visual and sound stimuli to execute several motor tasks related to their knee, including gait (two normal steps) during six sessions, with 5 mins of rest. The walking task has 4 trials per session, 7 s of duration. All subjects were asked to do not use their arms for getting extra support, to reduce brain activities related to upper limb movements. Additional sensors as goniometer and footswitch were used on the right leg to detect two phase of gait: preparation (- 1.5 s to 0 s, from gait onset or preswing), and stop (0 to +1.0 s, from offset). The rest phase was selected from 0 s to +2.5 s, using a stimulus signal as reference during stand rest position. In this work, only the gait planning and stand rest classes were considered.

2.2 Brain computer-interface

A BCI was proposed to recognize the gait planning, which is composed of the following stages: pre-processing, feature extraction, feature selection, and classification. Here, a weighted average filter (Plutscheller, Neuper and Berger, 1994; Lemm et al., 2005; Jiang et al., 2015) was applied on the pre-processing to improve the signal to noise ratio, using FC1, FC2, Cz, C3, C4, CP1, CP2, and Pz, in a similar way as done by (Xu et al., 2014; Jiang et al., 2015; Hortal et al., 2016). The other stages of the BCI are detailed in the next subsections.

2.3 Feature extraction

Several features were computed on Cz, CP1, CP2 and Pz locations to obtain the feature vector from time and frequency domains, such as: reference EEG raw (RF), mean absolute value (MAV), wavelength (WL), and band power (BP). Three features related to BP were computed on the frequency bands 0.1 to 4 Hz, 8 to 12 Hz, and 18 to 24 Hz. All features were obtained from the planning interval (-1.5 to 0 s from the onset reference), through a sliding window of 250 ms in length for each sample.

Figure 1. Block diagram of the proposed method to obtain a classification model from several setups.
2.4 Feature selection

An unsupervised method of low computational cost is used for dimensionality reduction (Delisle-Rodriguez et al., 2017), which may improve the performance during the analysis of clusters with uncertainty. Here, little modifications were introduced: 1) clusters dimension (from 10 to 80%) of the total features, increasing 10% to obtain the threshold value; 2) the redundant features are temporary removed on each iteration from the updated feature set, but they are continuously competing in next iterations with the new located redundancies.

2.5 Classification

A classifier based on LDA was used to recognize the gait planning intention, which is commonly applied in BCIs for motor intention recognition (Lotte et al., 2007). Three covariance matrices, diagonal, spherical, and full were used to search a suitable setup of classifier for each subject (Velu and de Sa, 2013), using the proposed method.

2.6 Statistical evaluation

Cross-validation technique (k = 3) was used on each subject to separate the sessions into both training and validation sets, in order to evaluate the approach in the BCI, during the gait planning recognition.

The indices ACC, TPR and FPR were used to evaluate the BCI performance, through an approach to select the suitable covariance matrix.

4 Results

EEG signals from five subjects were used on the BCI based on LDA classifier, in order to evaluate the approach during the gait planning recognition. After applying the spatial filter WAR and the feature extraction techniques on the locations Cz, CP1, CP2, and Pz an unsupervised method for dimensionality reduction was applied, which includes light modifications, described in subsection 2.4. Table 1 shows that a total of 24 features were analyzed through this method from the original cluster. Similar dimension outputs were obtained for three Subjects 1, 2 and 5. The features RF, WL, and BP were highly selected for all subjects, while MAV was little considered.

On the other hand, almost all subjects presented few contribution from some frequency bands on Cz. This low contribution can be observed in Figure 2. In addition, this figure shows a good contribution of the channels CP1, CP2 and Pz from the feature analyzed.

Table 2 shows that different setups were automatically adopted on LDA for each subject, where the full covariance matrix was more selected, during 3-fold. The diagonal covariance matrix presented on subject 1 the highest values of ACC (78%), TPR (89%) and FPR (27%). However, ACC values higher than 70% were obtain for almost all subjects. In contrast, almost all subjects presented TPR values between 54-59%. Moreover, TPR values were obtained between 18-30%.

Table 1. Selected features during the training stage.

<table>
<thead>
<tr>
<th>Sub</th>
<th>Full Features Size</th>
<th>New Features Size</th>
<th>Commonly Selected Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>17 - 20</td>
<td></td>
<td><em>FR, WL, MAV</em></td>
</tr>
<tr>
<td>2</td>
<td>17 - 19</td>
<td></td>
<td><em>FR, WL, MAV</em></td>
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<tr>
<td>3</td>
<td>14 - 20</td>
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<td><em>FR, WL, MAV</em></td>
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<tr>
<td>4</td>
<td>16 - 17</td>
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<td><em>FR, WL, MAV</em></td>
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<td>5</td>
<td>17 - 19</td>
<td></td>
<td><em>FR, WL, MAV</em></td>
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*0.1-4 Hz; *8-12 Hz; *18-24 Hz; * highly selected feature; WL, wavelength; MAV, mean absolute value; FR, free EEG reference; BP, band power.

5 Discussion

Several authors have demonstrated that the primary and supplementary motor areas play an important role in motor planning tasks (Pfurtscheller and Lopes Da Silva, 1999; Lew et al., 2012). In addition, many authors have reported the foot area motor on the center scalp, around the Cz, as the main areas (Pfurtscheller and Lopes Da Silva, 1999). This way, the locations Cz, CP1, CP2, and Pz were here adopted.
to recognize the gait planning intention. Patterns related to planning actions may present a high uncertainty due to the fact associated with intra-subject reaction time variability, EEG variability, and other unknown criteria such as event duration. Thus, unsupervised methods for clusters processing may be suitable to improve the training stage. After applying the algorithm for feature selection, higher contributions were obtained from CP1, CP2 and Pz locations, in accordance to Lew et al. (2012) during their study related to motor planning of upper limbs. For almost all subjects, Cz presented little contribution in some frequency bands, in contrast to Subject 1. Similar performance to the Subject 1, in the feature selection stage, was obtained on the Subjects 2 and 5, which present TPR value of 59%. However, Cz did not provide all BP features on the analyzed bands. Thus, it may be possible that Cz directly affect the BCI performance. However, specifically for Subjects 4 and 5, we observed a good classification during two iterations, but the recognition failed in one iteration. This effect could be related to noise or artifacts on the signals, as well as to some errors introduced by the same user before executing the random motor task. Thus, other indices as entropy should be explored to analysis these uncertain patterns. In accordance to Hortal et al. (2016), for all subjects ACC values higher than 70% were obtained, as well as TPR and FPR values between 54-59%, and 18-30% respectively. This previous work does not focus on decoding pre-movement states (from -1.5 to 0 s before the footswitch or angle release). Thus, a direct comparison is not easy. This way, other study proposed the combination of features based on amplitude at low frequency (MRCP from 0.1 to 1 Hz) and spectral information (from 8 to 13 Hz) to recognize gait planning, using a total of 10 channels (Shburea, Montesano and Mingleu, 2015). The authors used fastICA as pre-processing stage on the BCI, achieving accuracy of 70%.

Some works have used the spherical covariance matrix on the RDA classifier to recognize gait intention (Velu and de Sa, 2013), however, this matrix was not selected as a suitable setup for this approach. Additionally, the full matrix was more selected between the subjects, but the diagonal matrix presented the highest performance for Subject 1.

6 Conclusion

A BCI-based on non-supervised methods is proposed here to improve the learning stage during gait planning recognition. The method was evaluated on five subjects, using a BCI-based on Linear Discriminant Analysis (LDA) with three possible setups: diagonal, full, or spherical covariance matrix. The diagonal matrix presented the highest values of ACC (78%), TPR (89%), and FPR (27%) for one subject from the group under analysis. For the other subjects, values of ACC higher than 70% were obtained, and values of TPR and FPR between 54-59 %, and 18-30%, respectively.

This method may be also used with other classifiers such as SVM, KNN, RDA, among others. In future works, others robust indices to cluster distribution will be explored to provide a better classification model.

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Reference


