Generating Artificial EEG Signals To Reduce BCI Calibration Time

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Abstract

One of the major limitations of Brain-Computer Interfaces (BCI) is their long calibration time. This is due to the need to collect numerous training EEG trials for the machine learning algorithm used in their design. In this paper we propose a new approach to reduce this calibration time. This approach consists in generating artificial EEG trials from the few EEG trials initially available, in order to augment the training set size in a relevant way. The approach followed is simple and computationally efficient. Moreover, our offline evaluations suggested that it can lead to significant increases in classification accuracy when compared with existing approaches, especially when the number of training trials available is small. As such, it can indeed be used to reduce calibration time.

1 Introduction

In recent years, research efforts in Brain-Computer Interfaces (BCI) have led to the development of numerous BCI prototypes which have highlighted many promising applications, both in medical and non-medical domains. However, BCI still suffer from several limitations which make these prototypes usually far from being usable in practical applications [1]. One of these limitations is that many examples of the user's EEG signals must be recorded in order to calibrate the BCI, which is both inconvenient and time consuming. Currently, the best online BCI systems require a calibration time of about 20 minutes [2], which is still far too long. As a comparison, nobody would indeed use a computer mouse if it required a 20 minute-long calibration before each use.

A few recent works have proposed approaches to reduce [3, 4, 5] or suppress [6, 7, 8] this calibration time. However, these approaches require either data from numerous other users whose EEG signals have been previously recorded, or a large data set of past trials from the same user. Naturally, such data cannot be always available and we would ideally like the BCI to be efficient with very little training data even for a first-time BCI user. Therefore, there is a need for a method that can reduce the BCI calibration time without requiring numerous EEG data previously recorded. In this paper we propose such a method. It is a simple and efficient approach which consists in generating numerous artificial EEG signals from a few signals recorded from the user. Such new trials can then be used to augment the available training set.

2 Methods

BCI calibration times are long due to the need to collect numerous training EEG trials for the subsequent machine learning algorithms used in their design. This problematic need for large amounts of training data is not unique to the BCI field. It can also be found in other fields in which machine learning is involved, although the problem might be more severe for BCI. In these fields, one proposed approach dealing with this issue was to generate numerous artificial training data from the few actual training data available, and use it to augment the training

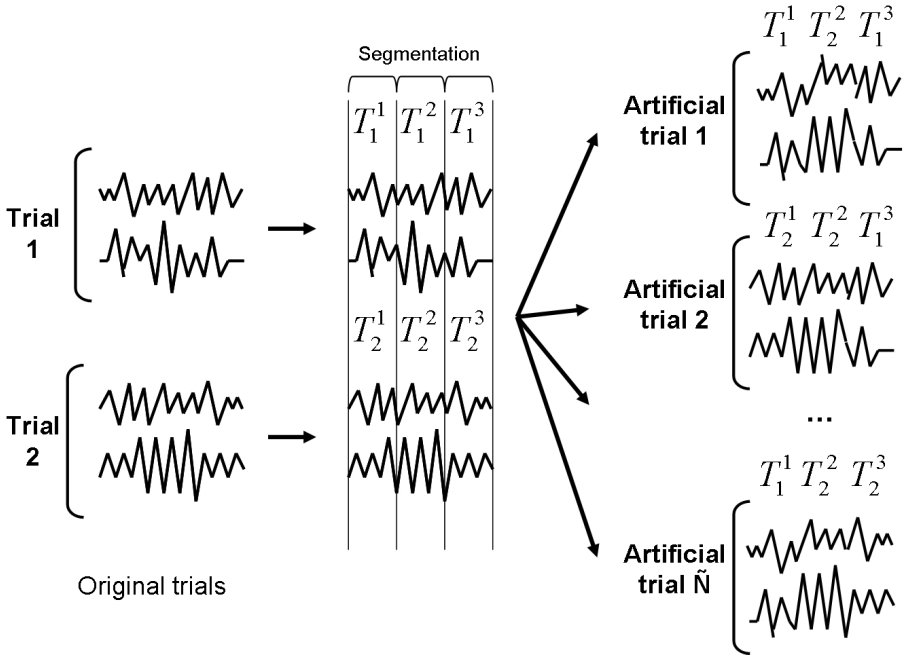

Figure 1: Principle of artificial EEG data generation for BCI design

set. This has been shown to lead to increased classification accuracies in fields such as speech or hand-writing recognition [9][10]. In this paper, we propose to follow a similar approach in order to generate artificial EEG data based on the method used in [9] for speech recognition. With this approach, we first divide each training EEG trial into several segments, and then generate new artificial trials as a concatenation of segments coming from different and randomly selected training trials. More formally, let us denote as $\Omega = \{T_i\}, i \in [1, N]$ the set of N EEG trials that are available for training. $T_i \in \Re^{C \times S}$, with S the number of samples in a trial, and C the number of channels. The first step consists in dividing the signals (from each channel) of each training trial T_i into K consecutive and non-overlapping segments $T_i^k \in \Re^{C \times S/K}, k \in [1, K]$. Then, from these segments, we can generate a new artificial trial $\tilde{T}_j$ as $\tilde{T}_j = [T^1_{R_1} T^2_{R_2} \dots T^K_{R_K}]$, where $[AB]$ denote the concatenation of the samples from segment A and B, and R_k is a randomly selected integer from $[1, N]$. The whole process is schematized in Figure 1. This simple approach enables us to generate a large number of new trials, different from the original ones, but still relevant and likely to be similar to future trials, as they were made from parts of real trials and have the same temporal structure. By adding these artificial trials to the original training trials, we can fill the feature space in a relevant way and hence ease the training of the subsequent machine learning algorithms. We thus expect this approach to give good classification performances even when only few EEG trials are initially available.

3 Evaluation and Results

We evaluated this approach offline on data set 2a from BCI competition IV, provided by the Graz group [11]. This data set comprises EEG signals from 9 subjects who performed left hand, right hand, foot and tongue Motor Imagery (MI). The EEG signals were recorded using 22 EEG channels. For the purpose of this study, only EEG signals corresponding to left and right hand MI were used. EEG signals were band-pass filtered in the 8-30 Hz frequency band using a 5th order Butterworth filter. Features were extracted using the Common Spatial Patterns (CSP) [12] algorithm (we used the filters corresponding to the 3 largest and smallest eigenvalues) from the 2-second time window starting 0.5 s after the cue. Features were classified using Linear Discriminant

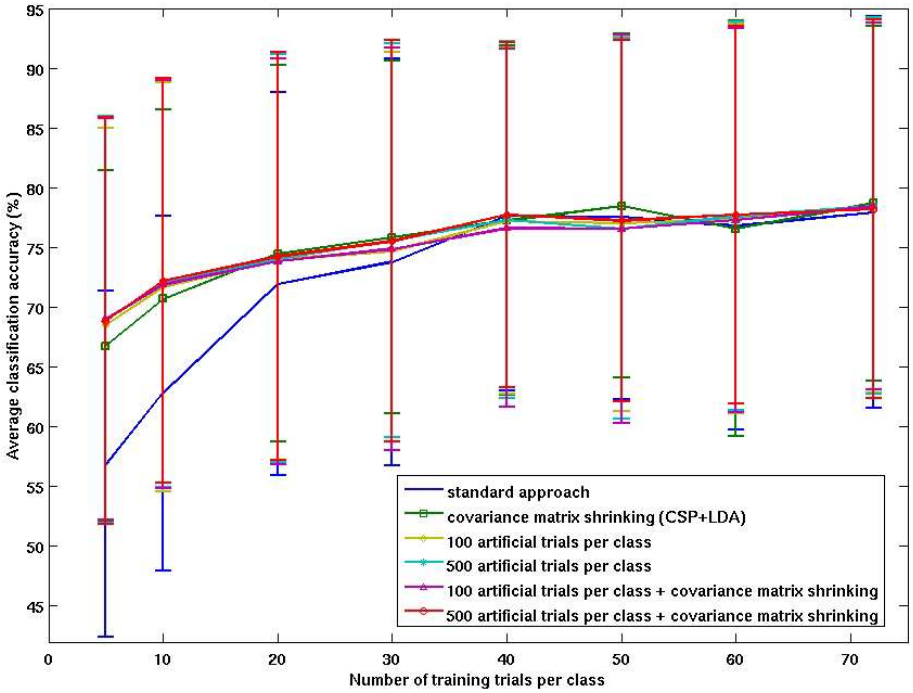

Figure 2: Classification accuracy (%) as a function of the number of training trials, for different approaches (standard approach, covariance matrix shrinking, artifical data generation).

Analysis (LDA).

We evaluated our approach on the test sets available (each comprising 72 trials per class), while using only the N first training trials from each class ($N \in [5, 10, 20, 30, 40, 50, 60, 72]$) to train CSP and LDA. In this context, we compared different approaches:

- The standard approach which directly trains CSP and LDA on the initially available training trials. This is what is done in most current BCI.
- Our approach based on Artificial Data Generation (ADG) as described above. We generated either 100 or 500 artificial EEG trials per class (using K=10 segments) and added them to the original training set.
- An approach which uses automatic Covariance Matrix Shrinking (CMS) for CSP and LDA, based on Ledoit and Wolf's method, as we did in [4]. This approach is specifically designed to obtain better estimate of covariance matrices with small training sets.
- A last approach which uses both ADG and automatic CMS for CSP and LDA.

As ADG involves random number generation, we repeated the ADG procedure 10 times, and averaged the classification accuracies hence obtained for each repetition. The average classification accuracies obtained for each method and training set size are reported on Figure 2. Results show that both ADG and CMS are more efficient than the standard approach, particularly when the number of training trials available is small (< 40). Globally, this difference is statistically significant ($p << 0.0001$ with a paired t-test). Using ADG, the accuracy obtained with only 10 trials is the same as that obtained with the standard approach when using 20 trials. Hence, as compared to the standard approach, ADG can effectively reduce the calibration time by 2. Using both CMS and ADG together leads to a slight improvement in accuracy as compared to using ADG alone, although this improvement is not statistically significant. When comparing ADG with CMS, it appears that when the number of training trials is really small (< 20), ADG leads to

higher classification accuracies. For a larger number of training trials, ADG and CMS appear to be rather similar. Overall, only ADG combined with CMS (with 500 artificial trials) leads to an accuracy that is significantly higher than that obtained by CMS alone ($p < 0.05$). Overall, these results suggest that artificial EEG trials generation is a simple and efficient approach to calibrate BCI systems with few training trials, thus effectively reducing the calibration time.

4 Conclusion

In this paper we have proposed a new approach to reduce the calibration time of BCI that are based on machine learning. This approach consists in generating artificial EEG trials from the few EEG trials initially available in order to augment the training set size in a relevant way. This is achieved by first dividing each available training EEG trial into several segments, and then by generating new artificial trials as a concatenation of segments coming from different and randomly selected training trials. This approach is simple, easy to implement and computationally efficient. Moreover, our offline evaluations suggested that it can indeed lead to significant increases in classification accuracy as compared to existing approaches, especially when the number of training trials available is small. As such, it can indeed be used to reduce the calibration time. Moreover, this approach is independant of the machine learning algorithms used subsequently and could therefore become a new tool in the repertoire of BCI designers. Future work will be dedicated to study more advanced methods to perform artificial trial generation, possibly based on data distortion and analogy as in [10], or exploiting a-priori knowledge on the mental tasks used to drive the BCI.

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