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Data fusion for paroxysmal events' classification from EEG

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HIGHLIGHTS

- Highly accurate classification of epileptic and non-epileptic EEG events.
- Comparison between EI and LI fusion schemes regarding this problem.
- Novel LI fusion to handle the high dimensionality and the limited number of samples.
- Study of the behavior of each scheme as a function of the dimensionality.
- Dimensionality reduction through PCA.

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ABSTRACT

Background: Spatiotemporal analysis of electroencephalography is commonly used for classification of events since it allows capturing dependencies across channels. The significant increase of feature vector dimensionality however introduce noise and thus it does not allow the classification models to be trained using a limited number of samples usually available in clinical studies.
New method: Thus, we investigate the classification of epileptic and non-epileptic events based on temporal and spectral analysis through the application of three different fusion schemes for the combination of information across channels. We compare the commonly used early-integration (EI) scheme – in which features are fused from all channels prior to classification – with two late-integration (LI) schemes performing per channel classification when: (i) the temporal context varies significantly across channels, thus local spatial training models are required, and (ii) the spatial variations are negligible in comparison to the inter-subject variation, thus only the temporal variation is modeled using a single global spatial training model. Furthermore, we perform dimensionality reduction either by feature selection or by principal component analysis.
Results: The framework is applied on events that manifest across most channels, as generalized epileptic seizures, psychogenic non-epileptic seizures and vasovagal syncope. The three classification architectures were evaluated on EEG epochs from 11 subjects.
Comparison with existing methods: Although direct comparison with other studies is difficult due to the different characteristics of each dataset, the achieved recognition accuracy of the LI fusion schemes outperforms the performance reported in the literature.
Conclusions: The best scheme was the LI with global model which achieved 97% accuracy.

1. Introduction

In clinical practice, electroencephalography (EEG) is used for the diagnosis and classification of interictal and ictal events (epileptic seizures) as well as the differentiation of the latter from other non-epileptic clinical events that may occur during recording, that mostly include vasovagal syncope (VVS) and psychogenic non-epileptic seizures (PNES). Electrodes, which act as sensors to detect the electrical activity, are attached to the scalp and provide both spatial and temporal information. There are two main approaches for fusing data from different EEG channels: early-integration and late-integration (Greene et al., 2007, 2008). In EI, which is com-

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monly used to exploit the spatiotemporal variation of EEG (Mporas et al., 2014, 2015; Pippa et al., 2014, 2015; Shoeb et al., 2004; Shoeb and Guttag, 2010) and the dependencies across channels, the data are fused directly after feature extraction. Feature vectors from each channel are combined and events are classified by one global classifier. On the other hand, in LI, events are classified for each channel by its local classifier and the results from these local classifiers are later fused in the decision layer (Greene et al., 2007, 2008; Shoeb et al., 2004).

Analysis of the electrical activity of the brain is very complex and difficult to summarize with a small number of variables extracted from EEG signals. As a result, analysis of EEG is usually accompanied by extraction of high dimensional feature vectors from the data. The dimensionality is further increased in EI approaches aiming to exploit the spatial information of EEG, where already high dimensional feature vectors from several channels are combined to a single large feature vector. The problem of high dimensionality coupled with the limited number of samples usually available in clinical studies, makes the analysis of multidimensional EEG signal a challenging task.

Thus in this paper, we compare the commonly used EI scheme and LI scheme and propose a new LI scheme to deal with the problem of high dimensionality in conjunction with limited number of samples. The proposed scheme combines information from all channels in order to train the classification model and thus is channel-independent. In general, the LI scheme keeps the dimensionality quite low, while the incorporation of a global training model allows the use of more training samples (by combining all channels). The performance of each scheme, as a function of the feature vector dimensionality, is also studied by performing feature ranking and selection prior to the classification using *t*-test as ranking method. The performance of the different schemes is investigated in relation to the problem of discrimination between clinical events of different nature, manifested by paroxysmal loss of consciousness. The differential diagnosis that a clinician usually faces is mainly that of a generalized epileptic seizure, a psychogenic non-epileptic seizure (PNES) and a vasovagal syncope (VVS). The diagnosis and management of paroxysmal loss of consciousness may be proven to be demanding, time consuming and expensive and finally, in spite of the extensive and exhaustive investigation, the underlying diagnosis may remain elusive (McKeon et al., 2006).

An epileptic seizure is a transient occurrence of signs and/or symptoms due to abnormal excessive or synchronous neuronal activity in the brain (Fisher et al., 2005), typically associated with EEG specific changes. The identification of epileptic events can be achieved by certain characteristic ictal neurophysiological patterns that appear during the episode. Psychogenic non-epileptic seizures (PNES) are paroxysmal events that result in loss of consciousness resembling epilepsy but without the characteristic electrical changes associated with the episodes of the latter (Szabo, 2013). Although historical information can sometimes support the discrimination between PNES and epileptic seizures, confident distinction on clinical grounds is frequently difficult. This is due to the insufficient event description by the patient and witnesses and the possible coexistence of epilepsy and PNES in the same patient. Vasovagal syncope (VVS) is a common type of syncope (Lewis, 1932). During a VVS characteristic EEG changes may include progressive generalized theta slowing of background rhythms, followed by diffuse delta activity of high voltage and appearance of progressively lower voltage rhythms until isoelectric suppression (Ammirati et al., 1998; Mecarelli et al., 2004). This pattern is progressively reversed after the end of the event when cerebral perfusion is restored. The changes captured by EEG recordings during a VVS do not include any ictal activity.

Despite such diagnostic uncertainty, the problem of automated discrimination between epileptic and non-epileptic pathological EEG events is rarely tackled in the literature. Relevant literature include an algorithm proposed in (Poulos et al., 2003) that is based on the correlation between features extracted from an appropriately selected epileptic EEG segment and the unknown ones in order to classify the latter into epileptic on non-epileptic. The extracted features used consist of auto-correlation coefficients and the achieved sensitivity and specificity are 83% and 90%, respectively. Two years later, the authors in (Papavlasopoulos et al., 2005) used a set of auto-correlation coefficients to train an LVQ1 neural network. The evaluation of the LVQ1 model on testing EEG segments resulted in 86% accuracy. The feature extraction methods of the aforementioned classification frameworks, as well as the achieved results were subsequently reviewed in (Papavlasopoulos et al., 2007) and statistical analysis using a chi-square test revealed the superiority of the LVQ1 method.

In a previous work (Pippa et al., 2014), both PNES and VVS events were examined in an attempt to extend the non-epileptic class. In order to automatically classify epileptic and non-epileptic (PNES and VVS) EEG epochs, a large set of temporal and spectral features was examined using an EI scheme for the combination of information across EEG channels using a dataset of 11 patients. Although such a spatiotemporal analysis captures holistically the change of the EEG signal, the limited number of the available samples was not enough to fully capture the spatiotemporal variation. This is a common problem in biomedical applications where the high dimensionality of the data hinders data modeling and representation (Erus et al., 2014).

Building upon our previous work (Pippa et al., 2014) in which an EI scheme was implemented, we now investigate two LI schemes performing per channel classification. The first scheme is based on the assumption that the temporal context varies significantly across channels, thus local training models are built, while the second scheme is based on the assumption that the spatial variations are negligible in comparison to the inter-subject variation, thus global training models can be used. Obviously this type of analysis can only be performed on events that generalize across EEG channels, such as the ones used in this study.

The rest of this paper is organized as follows. In Section 2 the evaluation data and the different fusion schemes for classification of epileptic and non-epileptic events are presented. Section 3 provides details about the validation and the achieved results. Finally in Section 4 we conclude this work.

2. Material and methods

2.1. Data

In this paper, we use EEG recordings acquired by the Department of Clinical Neurophysiology and Epilepsies in St Thomas' Hospital, London, UK from 11 patients for the needs of the ARMOR project (ARMOR, 2016). For investigation purposes the epileptic and non-epileptic events were manually annotated and isolated from the recordings. The epileptic events were derived from patients diagnosed with Idiopathic Generalized Epilepsy (IGE) with absence seizures. The isolated epileptic events consist of Generalized Spike Waves (GSW) derived from the epileptic group. The non-epileptic events were derived from 2 patients with VVS and 5 patients with PNES. For all the examined subjects, at least one typical epileptic or non-epileptic event appear during the recording. The recordings were performed using conventional AgCl EEG electrodes positioned according to the extended international 10–20 system. For the analysis we used EEG channels Fp2, F8, F4, T4, C4, A2, P4, T6, O2, Fp1, F7, F3, A1, C3, T3, P3, T5, O1, Fz, Cz, and Pz. Note that in this study,A1 and A2 are midtemporal active electrodes. The montage is referenced to C3+C4/2. During the training and test phases of our classification