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Detection of temporal lobe epilepsy using support vector machines in multi-parametric quantitative MR imaging

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ABSTRACT

The detection of MRI abnormalities that can be associated to seizures in the study of temporal lobe epilepsy (TLE) is a challenging task. In many cases, patients with a record of epileptic activity do not present any discernible MRI findings. In this domain, we propose a method that combines quantitative relaxometry and diffusion tensor imaging (DTI) with support vector machines (SVM) aiming to improve TLE detection. The main contribution of this work is two-fold: on one hand, the feature selection process, principal component analysis (PCA) transformations of the feature space, and SVM parameterization are analyzed as factors constituting a *classification model* and influencing its quality. On the other hand, several of these classification models are studied to determine the optimal strategy for the identification of TLE patients using data collected from multi-parametric quantitative MRI.

A total of 17 TLE patients and 19 control volunteers were analyzed. Four images were considered for each subject (T1 map, T2 map, fractional anisotropy, and mean diffusivity) generating 936 regions of interest per subject, then 8 different classification models were studied, each one comprised by a distinct set of factors. Subjects were correctly classified with an accuracy of 88.9%. Further analysis revealed that the heterogeneous nature of the disease impeded an optimal outcome. After dividing patients into cohesive groups (9 left-sided seizure onset, 8 right-sided seizure onset) perfect classification for the left group was achieved (100% accuracy) whereas the accuracy for the right group remained the same (88.9%).

We conclude that a linear SVM combined with an ANOVA-based feature selection + PCA method is a good alternative in scenarios like ours where feature spaces are high dimensional, and the sample size is limited. The good accuracy results and the localization of the respective features in the temporal lobe suggest that a multi-parametric quantitative MRI, ROI-based, SVM classification could be used for the identification of TLE patients. This method has the potential to improve the diagnostic assessment, especially for patients who do not have any obvious lesions in standard radiological examinations.

1. Introduction

Magnetic resonance imaging (MRI) is a powerful tool for the evaluation of patients with brain disorders and neurological diseases. For those with temporal lobe epilepsy (TLE), the most common type of epilepsy in adults [1], it is the entry point to a clinical workflow that may conclude with temporal lobe surgery and an improved quality of life. Finding evidence of seizures on MRI is a clear diagnostic element for TLE, however this task is not easy given that epileptogenic lesions are often small and can be missed, they can be uncertain due to subtle intensity changes, or only perceptible after image post-processing. Furthermore, due to

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the multi-factorial nature of the disease, the localization and type of the lesions can vary from patient to patient.

While the visual inspection is a common radiological procedure for the diagnosis of TLE, it has been shown that the detection of brain pathologies associated with TLE can be improved with computer-assisted, automatic multi-parametric MRI analysis. For example, the detection of changes in the shape, volume and intensity of the hippocampus has been studied using structural T1- and T2- weighted images [2–5]; White matter abnormalities have been detected with diffusion tensor imaging (DTI) in TLE patients [6–8], and DTI has been employed concurrently with functional MRI (fMRI) to perform language lateralization of TLE patients [9].

A support vector machine (SVM) is a classifier that uses *a priori* knowledge in the form of group labels (supervised learning) and produces a *decision boundary* that can be used to determine the label of new examples [10,11]. Recent studies have examined the possibility of improving TLE detection using SVMs on MRI data. For example Focke et al. [12] show correct patient lateralization (left vs. right seizure onset) using SVMs on T1-weighted and DTI data. In addition to lateralization, Keihaninejad et al. [13], demonstrate the identification of TLE cases with hippocampal atrophy from cases without it using SVM on regional volumes obtained from T1-weighted MRI.

In this context, the goal of the current study is to explore TLE detection using multi-parametric quantitative MRI and support vector machines. For that purpose, quantitative maps of T1, T2, as well as fractional anisotropy (FA), and mean diffusivity (MD) are estimated for every participating subject. Quantitative MRI measures biophysical tissue properties and it has the potential to be more sensitive to TLE detection than T1- and T2-weighted images. Additionally, quantitative measurements are independent of experimental settings and thus comparable between different scanners, institutions and over different points in time [14].

2. Methods

2.1. Overview

All subjects in this study underwent an imaging protocol approved by the Office of Research Ethics of Western University (Canada). The imaging protocol comprised DESPOT1, DESPOT2 [15,16] and DTI sequences, resulting image data being processed to obtain four different quantitative maps: T1, T2, fractional anisotropy (FA) and mean diffusivity (MD). Anatomical atlas-based labeling was used to define ROIs on each one of the quantitative maps and subsequently to measure and extract regional features.

Given that the number of features exceeded the number of subjects (936 features, 36 subjects), two different feature selection methods were explored to discard irrelevant or uninformative features. Then, the feature space was further reduced using principal component analysis (PCA).

An SVM was trained/tested on the filtered feature space using a leave-one-out cross-validation strategy (LOOCV), where the SVM was tasked with predicting the label (patient or control) for the omitted subject (Fig. 1). Once all subjects were evaluated, sensitivity, specificity and classification accuracy were measured and reported. This procedure was repeated for each *classification model* obtained by the combination of the following elements:

- the image that originates the features (T1, T2, FA, MD, or all combined)
- the method to select features
- the cardinality of the requested feature set [K]
- the use of PCA to reduce the feature space
- the type of SVM

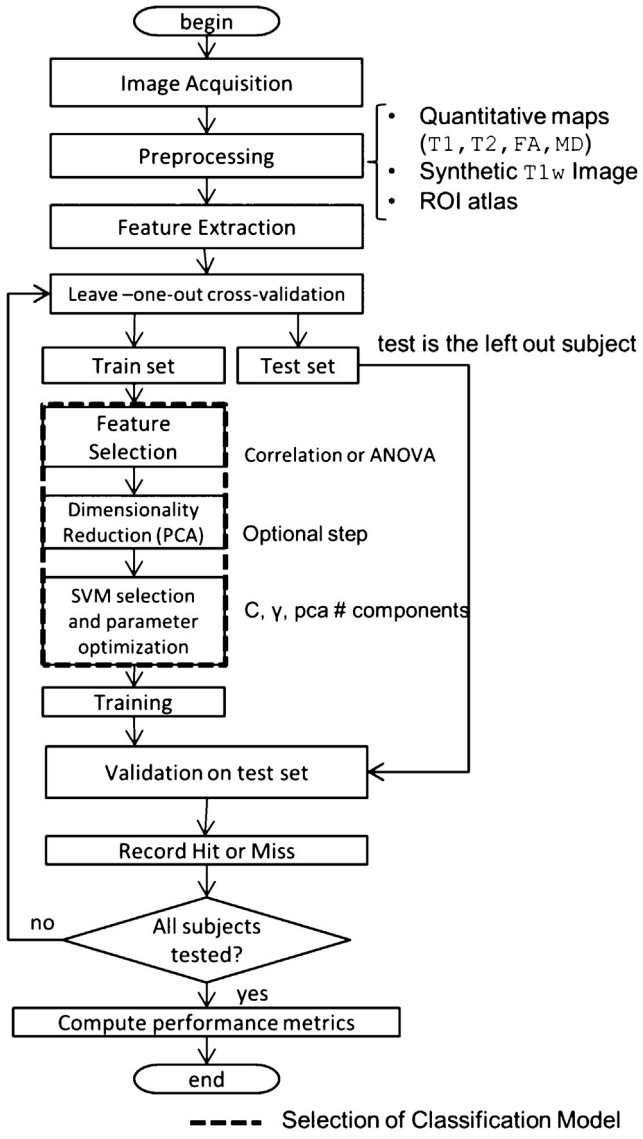

Fig. 1. Method. The preprocessing and feature extraction steps are the same for all the experiments and therefore they are executed only once. Each of the experiments described in the current work corresponds to different instances of the leave-one-out cross-validation (LOOCV) loop. The model selection stage determines the feature space, its dimension (PCA-reduced or not), and the parameters that constitute the classification model. 8 models in total are evaluated for each classification experiment. These models are evaluated using performance metrics that are collected at the end of each LOOCV loop.

A detailed comparison among classification models is reported in the Results section along the best classification scenarios. Specific recommendations regarding the optimal model are given in the Discussion section. In addition, an analysis of the elements constituting a classification model and their influence in the classifiers performance is also discussed. Finally, the features relevant for classification are analyzed and their clinical significance is considered.

2.2. Participants

Thirty-six individuals participated in this study, 19 of whom were control volunteers (age 32 ± 10, 12 male, 7 female) and 17 TLE patients (age 35 ± 10, 8 male, 9 female). All the patients had lateralizable seizures (confirmed by EEG) and all of them were eligible for temporal lobectomy (9 left, 8 right). Preoperative MRI and