Analysis of Brain White Matter Hyperintensities

Mariana Bento, Letícia Rittner, Roberto Lotufo
School of Electrical and Computer Engineering
UNICAMP
Campinas, Brazil
Email: marianapbento@gmail.com, lrittner@gmail.com, lotufo@unicamp.br

Simone Appenzeller
Department of Medicine, Rheumatology
UNICAMP
Campinas, Brazil
Email: appenzellersimone@yahoo.com

***Abstract*—This paper explores the use of the Support Vector Machine (SVM) for the identification and classification of white matter hyperintensities (WMH) in MRI scans of human brains. SVM classifier was applied to a dataset of texture attributes extracted from 330 annotated ROIs of normal white matter and of white matter hyperintensities with ischemic and demyelinating etiology. Experiments have shown that the SVM classifier is suitable for this application. Although, further experiments demonstrated that a combination of classifiers would probably improve the achieved results.**

***Keywords*-Magnetic Resonance Imaging; Texture attributes; Support Vector Machine**

I. Introduction

White matter hyperintensities (WMH) are a common finding in brain Magnetic Resonance Imaging (MRI) in both asymptomatic and neurologic symptomatic patients [1]. Etiologies vary according to age, but ischemic and demyelinating nature are more frequently observed. The specialist usually takes into account additional clinical information from patients to manually accomplish the classification task. Thus, to develop an automatic WMH classifier it is necessary to combine methods from different research areas, such as digital image analysis and pattern recognition.

One possible approach is to use texture analysis (TA), followed by a classification step, in order to compare normal white matter, demyelinating WMH (observed in multiple sclerosis patients) and WMH observed in patients with ischemic lesions. TA is a branch of image processing [2] that has been applied to many medical images applications [3] and classification is one of the most important tasks in machine learning. In medical imaging, there are many works on the literature using classifiers to assist medical staff to achieve high efficiency and effectiveness [4].

This paper presents a technique based on texture features extraction and the SVM classifier to distinguish normal white matter, white matter hyperintensities in multiple sclerosis, white matter hyperintensities in patients with ischemic lesions. Once we have a trained classifier, we will use it to study white matter lesions, whose etiology are unknown.

This paper is organized as follows. We describe the applied methods including aspects of feature extraction and classification in section II. The experiments and results are covered on section III. Finally, in last section, concluding remarks and future works are presented.

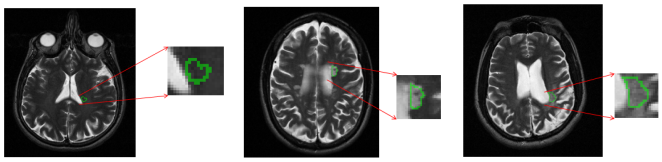
II. Method

The identification and classification of white matter hyperintensities will be subdivided into three main steps: regions of interest extraction, texture attributes extraction and the classification procedure. The lesion identification will be treated as a classification problem of 2 classes: lesion or no lesion. The lesion classification procedure also presents 2 classes: WMH in multiple sclerosis and WMH in isquemic patients.

A. Database

Our image database was acquired from January 2003 to December 2006. T2-weighted MRI were obtained in the axial plane (3 mm thick, flip angle 120 degrees, repetition time 6800 ms, echo time 129 ms).

Regions of Interest (ROIs) were manually selected and annotated by an expert representing 2 different datasets. The first one is composed by ROIs of normal white matter and WMH from ischemic and demyelinating etiology nature (Fig. 1). The second dataset is composed by Systemic Lupus Erythematosus lesions, identified by its localization (periventricular or subcortical), and with unknown etiology. ROIs present different sizes and shapes and contain only the one type of tissue.



(a) Normal White Matter sample (b) Ischemic etiology sample (c) Demyelinating etiology sample

Fig. 1. Database samples and ROIs extraction example

B. Attributes Extraction

The feature extraction was performed through TA approach based on the Gray Level Co-occurrence Matrices (GLCM), Haar Wavelet, Run Length Matrix, Gradient and histogram parameters [5]. A total of 60 texture parameters were computed for each ROI using the software Mazda[1] and normalized between 0 and 1.

[1] www.eletel.p.lodz.pl/programy/mazda/

C. Classification

The SVM classifier was developed based on texture features of normal white matter, ischemic etiology lesion and demyelinating etiology lesion. We chose SVM classifier, since it shows excellent performance in many applications described in the literature [6]. SVM is a supervised learning method that can be applied to classification or regression. It presents several method's variations according to kernel and parameters selection. In this paper we use linear SVM and performed a grid search to find the best parameter configuration [7]. In order to assess the classifiers accuracy based on randomly sampled partitions of the given data, it was used 10-fold cross validation method.

III. Experiments and Discussion

The first experiment was conducted in order to measure the SVM accuracy and execution time while performing different classification tasks. The first task was to distinguish between lesion and no lesion classes. We call this task lesion identification. The second task was to differentiate between ischemic and demyelinating lesions, called lesion classification. We also tried to perform both tasks at a time, designing a classifier to distinguish between 3 classes: normal tissue, WMH with ischemic etiology and WMH with demyelinating etiology, called ROIs analysis. Results of the first experiment can be seen in table I. We achieved accuracy rates of 98.18% for lesion identification, 91.79% for lesion classification and 89.69% for ROI analysis, when using the SVM classifier.

A second experiment was conduct to compare the SVM performance with other classifiers. The main purpose was to verify if the use of fast and non parametric classifiers, such as Optimum Path Forest (OPF) and Nearest Neighbor (1-NN), provide similar results. Not only their accuracy were compared, but also their execution time and their behavior with a varying feature space size.

Preliminary results can be seen in table II and in Fig. 2. We observed that SVM presents higher execution time and lower accuracy rates. Further investigation could be useful to understand why SVM presented the worst accuracy. However, it is possible to notice by observing their confusion matrix that SVM misclassified normal white matter with ischemic lesions, while OPF and 1-NN mostly confused WMH (ischemic and demyelinating etiology) suggesting that a combination of classifiers could improve the achieved results.

A last experiment is planned in order to classify Systemic Lupus Erythematosus (LES) lesions according to its etiology. Once we have a trained classifier to distinguish lesions with ischemic or demyelinating etiology, periventricular and subcortical LES lesions could be classified as one of the known classes. Preliminary results have showed that may be possible to classify lesions with undetermined etiology into one of know classes.

IV. Concluding Remarks

The experiments have shown that texture analysis (TA) and the SVM classifier are useful techniques to identify and classify white matter and also to study lesions, whose etiology are unknown. However, comparative experiments have shown that SVM is not the best classifier for this application, since OPF and 1NN achieved better results. In order to increase the classification accuracy and understand better the problem, further investigation is being planned, such as the combination of different classifiers and the inclusion of a feature selection procedure.

TABLE I
Lesions Identification and Classification

Procedure	Accuracy (%)	Execution Time (s)
Identification	98.08	0.07
Classification	91.79	0.13
ROIs analysis	89.69	26.06

TABLE II
Comparison between SVM, 1NN and OPF to perform the ROIs analysis

Classifier	Accuracy (%)	Execution Time (s)
SVM	89.69	26.06
1NN	92.42	0.02
OPF	92.42	0.2084

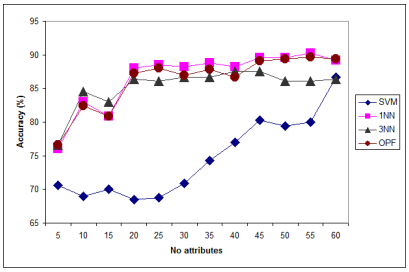


Fig. 2. Classification accuracy given an increasing number of attributes. Number of attributes varies from (5) until the complete dataset (60)

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