Classification of white matter lesions in systemic lupus erythematosus using support vector machines

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Abstract – This paper aims to develop a possible mechanism to distinguish white matter hyperintensities (WMH) in systemic lupus erythematosus (SLE) between demyelination and ischemia etiologies. Texture attributes extracted from Magnetic Resonance Images formed the dataset to classification procedure. We achieve an accuracy rate of 0.93 to classify normal white matter, white matter hyperintensities in multiple sclerosis and in ischemic patients using support vector machine (SVM). WMH from SLE were mainly classified as demyelinating and it was not detected any reliable difference between results obtained on periventricular or subcortical images.

Key-words: lupus, etiologies, texture, SVM.

1. 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. Processing and automatic analysis of MRI images, however, is a non-trivial task, due to complexities of the underlying factors, including variable staining procedures and practices, illumination variations, diversity in imaging devices, and the ultimate goal of the analysis. To accomplish manually the classification task, the specialist usually takes into account additional clinical information from patients, such as age, physical exam and history. 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.

White matter hyperintensities (WMH) are frequently observed in systemic lupus erythematosus (SLE), however their etiology is still unknown. Ischemia and demyelination have been proposed as possible etiologies. One possible approach is to use texture analysis (TA) to compare WMH observed in SLE with WMH of multiple sclerosis (MS), WMH of ischemic patients and with normal white matter. TA is a branch of image processing, which seeks to reduce image information by extracting texture descriptors from the image [2]. The use of a Support Vector Machine (SVM) as classifier of all WMH texture attributes can give us a clue about the etiologies of SLE white matter hyperintensities. SVM is a class of supervised learning methods that can be applied to classification or regression [3]. SVM performs classification by constructing a set of hyper planes in a high dimensional space that optimally separates the data into different categories. A classification task usually involves separating data into training and testing sets. The goal of SVM is to produce a model based on the training data, which predicts the target values of the test data given only the test data, attributes.

This paper propose a technique based on image analysis (texture features extraction), and pattern recognition (SVM) to classify SLE lesions between demyelination and ischemic etiologies.

2. Methodology

The Regions of Interest (ROIs) dataset of MS, Ischemic, Normal, periventricular and subcortical LSE were extracted manually from T2-weighted MRI volumes (2.0 Tessla Elscint) of individuals with WMH 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, matrix
The second step performed was the feature extraction, through TA approach based on the Gray Level Co-occurrence Matrices (GLCM), Haar Wavelet, Run Length Matrix, Gradient and histogram parameters. A total of 256 texture parameters were computed for each ROI using the software Mazda.

Then a SVM classifier was developed based on texture features of normal white matter and WMH in MS and isquemic patients. The dataset was subdivided into two parts: training and testing datasets. The first dataset was the training dataset, and consisted of 90 ROIs of WMH. The second dataset was a qualifying test set, consisting of 20 ROIs of WMH. These two datasets come with expert annotations indicating ischemic or demyelinating WMH.

The following step was to classify unknow etiology data, 37 periventricular and 53 subcortical SLE, between the possible classes: MS, Isquemic and Normal. The developed methodology steps are displayed on Figure 1.

![Developed methodology procedure](image)

3. Results and Discussion

We achieve an accuracy rate of 0.93 to distinguish normal white matter and WMH in MS and Isquemic patients using SVM technique. Figure 2 shows the rate of correct classified and misclassified data. On the procedure of classify unknow etiology data, we obtain the following results for periventricular SLE data: 78% were classified as demyelination, 11% as ischemia and 11% as normal white matter. Indeed, the results obtained to subcortical SLE lesions are 72% classified as demyelination, 11% as ischemia and 17% as normal white matter as Figure 3 depicts.

In summary, the results shown that periventricular and subcortical SLE lesions are mostly classified as demyelinating in nature. The main difference between periventricular and subcortical results is that subcortical SLE present more samples classified as normal white matter than classified as ischemia. On the other hand, periventricular SLE present equal number of samples classified on both classes.
4. Conclusions

In this work, we have investigated the usage of SVM classifier to analyse the possible etiologies of SLE lesions. The obtained accuracy is promising and we conclude that TA and SVM classifier are useful techniques to determine etiology of WMH in SLE. The difficulties of the developed methodology was to choose for best SVM type and parameters and to find an optimized set of attributes. In future works, we will study and include clinical parameters on the classification procedure, such as age and disease duration, to verify other relevant information about the input data.

References