Analysis of Brain White Matter Hyperintensities using Image Processing and Pattern Recognition Techniques

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Abstract – Lesions in the brain white matter, called white matter hyperintensity (WMH), can cause a significant functional deficit. We propose here an automatic method for WHM analysis in order to distinguish regions of interest between normal and non-normal white matter (identification task) and also to distinguish different types of lesions based on their etiology: demyelinating or ischemic (classification task). The method combines texture analysis with the use of classifiers, such as Support Vector Machine (SVM), Nearst Neighboor (1NN), Linear Discriminant Analysis (LDA) and Optimum Path Forest (OPF). Experiments with real brain MRI data showed that the proposed method is suitable to identify and classify the brain lesions.

Keywords – White Matter Hyperintensity; Brain White Matter; Magnetic Resonance Imaging; Lesions Etiology; Demyelinating; Ischemic; Texture analysis; Classifiers.

1. Introduction

White matter hyperintensities (WMH) are commonly found in brain Magnetic Resonance Imaging (MRI) in both asymptomatic and neurologic symptomatic patients [2]. Their etiology varies according to age, but ischemic and demyelinating are more frequently observed. The analysis of white matter intensities in the brain through MRI, however, is a non-trivial task, due to the complexity of underlying factors: variable staining procedures and practices, diversity in imaging devices, and the ultimate goal of the analysis. The specialist usually takes into account additional clinical information from patients, such as age, physical exam and history and also medical images from different modalities to manually accomplish the classification task. Thus, in order to automatically analyze white matter hyperintensities it is necessary to combine methods from different research areas, such as digital image analysis and pattern recognition.

Klöppel presents a comparison of different methods for the detection of WMH in MRI based on intensity features and Support Vector Machine (SVM) and k-nearest neighbor (kNN) classifiers [7]. Anbeek proposes a method to automated segmentation of white matter lesions in cranial MR images [1]. The method generates probability maps representing the probability per voxel being part of a white matter lesion. Another work compares automatic methods to detect multiple sclerosis lesions in the brain MR images [15]. Those and other related works in the literature generally propose methods to automatically identify white matter lesions caused by a specific disease with a known etiology. There is no work in the literature that combines image processing and pattern recognition techniques to analyze lesions according to their etiology.

2. Main Goal

We present here a technique based on texture analysis and a classification procedure to distinguish between normal and non-normal white matter tissue, denoted identification task, so as to distinguish white matter lesions based on their etiology, called classification task. Texture analysis is a branch of image processing [6] that has been used in many medical images applications [3], such as tissue characterization [9] and segmentation of diffuse lesions of the brain’s white matter [8]. Classification is one of the most important tasks in machine learning field. In medical imaging, there are many works on the literature using classifiers to assist medical staff to achieve high efficiency and effectiveness.

The method combines texture analysis and a classification procedure by using SVM, LDA, OPF and 1NN classifiers in order to compare their accuracy rates. We also performed experiments with other classifiers, such as Gaussian Naive Bayes, but they did not achieve acceptable results. The method was developed in Adessowiki [10], a collaborative environment for development and documentation of scientific computing algorithms.
3. Methods

The proposed analysis of white matter hyperintensities received as input the image database containing manually segmented regions of interest (ROIs) and gave as output the corresponding class of each ROI. The proposed method was subdivided into three main steps. The first one was represented by the image acquisition procedure using the MRI scanner, followed by the manual segmentation performed by a specialist. The second step was the texture analysis where the texture attributes were extracted from each segmented region of interest, followed by the attribute selection procedure. The last step comprised the WMH identification and the WMH classification tasks.

3.1. Image Acquisition and Manual Segmentation

Our image database was formed by T2-weighted MRI and it was 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. It is composed by ROIs of normal white matter, WMH with ischemic etiology and WMH with demyelinating etiology (Figure 1). ROIs presented different sizes and shapes and contained only one type of tissue.

![Figure 1. Images Samples](image)

3.2. Attributes Extraction and Selection

One of the most difficult tasks in the image analysis field is to define a set of attributes that describes effectively a region in an image, and can be used to classify the different patterns presented in the analyzed region [12]. In the literature, it is possible to find three different types of attributes that can be extracted from an image: texture, color and shape attributes. Since WMH do not present a specific shape and the MR images are gray-scale, shape and color attributes could not be applied in this problem. Thus, only texture attributes were used.

The texture attributes extraction was performed based on different texture analysis approaches. The statistical approach, for example, is based on the gray level histogram of the image, while the Gray Level Co-occurrence Matrices (GLCM) approach analyze the occurrence of pairs of pixels with gray level i and j in a image given a specific offset and orientation between them. The Run Length Matrix approach, on the other hand, represents the frequency in with a specific number of pixels with the same gray level occurs consecutively in a determined direction. Other well-known texture extraction approach is the signal processing one, based on the Haar Wavelet decompositions of the studied region.

A total of 88 texture attributes were computed for each ROI based on those approaches, and then normalized between 0 and 1. The attributes extraction was performed using the software Mazda, a computer program for calculation of texture parameters in digitized images. We also applied an attributes selection procedure in order to discard irrelevant or redundant attributes by using the decision tree algorithm. The decision tree algorithm [5] were originally intended for classification, but nowadays is largely used as an attributes selection method.

3.3. White Matter Hypertensities Identification and Classification

The final step of the proposed methodology comprised the identification task, that aims to distinguish the previous segmented ROIs between normal and non-normal white matter, and the classification task, that aims to distinguish ROIs containing WMH based on their etiology: demyelinating or ischemic. In order to accomplish those tasks, the classifiers SVM, OPF, LDA and 1NN were designed based on texture features of normal white matter, ischemic WMH and demyelinating WMH.

Support Vector Machine (SVM) is a supervised learning method that can be applied to classification or regression. It performs classification by constructing a set of hyperplanes in a high dimensional space that optimally separates the data into two categories [14]. The Optimum Path Forest (OPF) [11] classifier, on the other hand, models the data classification task as a partition problem in a graph and can be used as supervised or unsupervised classification method. We also performed
experiments by using the Linear Discriminant Analysis (LDA). LDA is parametric and statistical method that can be used to attributes selection, so as to the classification procedure. At least, we also tried to execute the classification task by using the Nearest Neighbor classifier (1NN). The 1NN decision rule assigns to an unclassified sample point the classification of the nearest of the previously classified points [4]. The 1NN classifier presents many conceptual similarities to the OPF classifier, therefore it is possible to obtain the 1NN classifier by considering all training samples of OPF as prototypes [13].

We executed the WMH identification and the WMH classification tasks using SVM, OPF, LDA and 1NN classifiers in order to compare their achieved accuracy rates. It was used a 10-fold cross validation method to assess the classifiers accuracy based on randomly sampled partitions of the given data.

4. Experiments and Results

The experiments were conducted in order to measure the classifiers accuracy while performing different tasks. The first experiment comprises the WMH identification, while the second one represents WMH classification. The final experiment comprehends both tasks, in with the WMH identification and WMH classification are performed simultaneously. The first experiment was to distinguish ROIs between normal and non-normal white matter tissue. We call this task lesion identification and the results can be seen in Table 1. We achieved similar accuracy rates for OPF and 1NN classifiers (98.24%), and 99.35% for SVM using the entire set of 88 attributes. When we use a optimize set of attributes (31 attributes selected by the decision tree algorithm), the accuracy rates of OPF, 1NN and LDA increased, while SVM rate decreased.

<table>
<thead>
<tr>
<th>Class.</th>
<th>Acc (%)</th>
<th>Acc - Att Selection (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>99.35</td>
<td>98.93</td>
</tr>
<tr>
<td>OPF</td>
<td>98.24</td>
<td>98.28</td>
</tr>
<tr>
<td>1NN</td>
<td>98.24</td>
<td>98.61</td>
</tr>
<tr>
<td>LDA</td>
<td>98.64</td>
<td>98.96</td>
</tr>
</tbody>
</table>

Table 1. WMH Identification: distinguish normal from non-normal white matter.

The second experiment was to differentiate between ischemic and demyelinating lesions, called lesion classification. As we can check on Table 2, the SVM presented the best accuracy rate using both the entire set of attributes or a set of 33 attributes.

<table>
<thead>
<tr>
<th>Class.</th>
<th>Acc (%)</th>
<th>Acc - Att Selection (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>86.76</td>
<td>86.76</td>
</tr>
<tr>
<td>OPF</td>
<td>81.28</td>
<td>81.52</td>
</tr>
<tr>
<td>1NN</td>
<td>80.28</td>
<td>81.15</td>
</tr>
<tr>
<td>LDA</td>
<td>80.52</td>
<td>81.01</td>
</tr>
</tbody>
</table>

Table 2. WMH Classification: distinguish different types of lesions based on their etiology: demyelinating or ischemic.

We also tried to perform both tasks simultaneously, designing a classifier to distinguish between 3 classes: normal tissue, WMH with ischemic etiology and WMH with demyelinating etiology. Results of this final experiment can be seen in Table 3. SVM presented the best result without attributes selection procedure (91.7%).

<table>
<thead>
<tr>
<th>Class.</th>
<th>Acc (%)</th>
<th>Acc - Att Selection (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>91.70</td>
<td>88.74</td>
</tr>
<tr>
<td>OPF</td>
<td>85.95</td>
<td>87.92</td>
</tr>
<tr>
<td>1NN</td>
<td>88.06</td>
<td>87.57</td>
</tr>
<tr>
<td>LDA</td>
<td>87.09</td>
<td>87.78</td>
</tr>
</tbody>
</table>

Table 3. WMH Identification and classification at a time: distinguish between normal white matter, ischemic etiology lesion and demyelinating etiology lesion.

The experiments showed that the attributes selection step increased the classifiers accuracy rates, except for the SVM classifier. This can be explained by the fact that the SVM performs this procedure intrinsically, during the construction of the classifier model. The 1NN and OPF classifiers generally achieved similar accuracy rates, since they present many conceptual similarities, as commented on the previous section. There is no best overall classifier, since a different classifier achieved the best result for each task.

It is also possible to notice by analyzing the achieved results that the lesions classification task is the most difficult task to handle, suggesting that it is easier to distinguish between normal white matter and white matter hyperintensity than to correctly classify different types of lesions according to its etiology.
5. Conclusions

The experiments have shown that texture analysis and 1NN, OPF, LDA and SVM classifiers are suitable techniques for this application. We performed two different approaches to solve this problem: to identify and classify lesions in a single step or to identify and classify lesions into two different steps. In order to increase the classification accuracy and understand better the problem, further investigation is being planned, such as the extraction of other attributes, the application of other classifiers and also the combination of different classifiers. We are also planning to increase the image database in order to validate the method and to analyze its robustness.

6. Acknowledgments

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References


