Texture Descriptors and Pattern Recognition Classifiers based Analysis of White Matter Hyperintensity in MR Images

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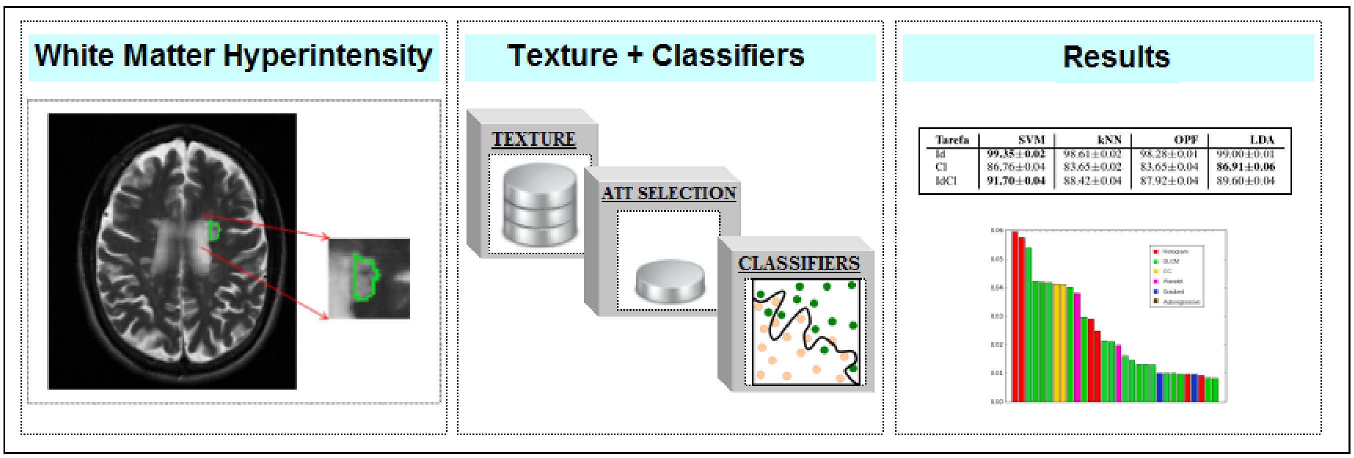

Fig. 1. Teasing of our method: from the manually segmented region of interest containing white matter hyperintensity or normal white matter (left), the texture features are extracted and applied into a classification procedures (middle), producing effective results (right).

***Abstract*—Lesions in the brain white matter, called white matter hyperintensity (WMH), can cause a significant functional deficit. This dissertation[1] proposes a method for brain white matter lesions analysis in order to distinguish regions of interest between normal and abnormal brain white matter, called lesion identification task, and also to distinguish different types of lesions based on their etiology: demyelinating or ischemic, called lesion classification task. The method combines texture analysis with the use of classifiers, such as Support Vector Machine (SVM), k-Nearst Neighboor (kNN), 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*-Hyperintensity; White Matter; Brain; Magnetic Resonance; Lesions Etiology; Demyelinating; Ischemic; Texture analysis; Classifiers.**

I. Introduction

White matter hyperintensities (WMH) are commonly found in brain Magnetic Resonance Imaging (MRI) in both asymptomatic and neurological symptomatic patients [1]. The frequency in which those lesions are detected may have an association with the disease activity, or with cognitive disturbs, however this research subject is still controversial, making harder to correlate the clinical manifestations with the neuroimaging findings [2].

The analysis of WMH 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 exams, medical 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 [3]. Anbeek proposes a method to perform automatic segmentation of WMH in cranial MR images [4]. The method generates probability maps representing the probability of each voxel being part of a WMH. Another work compares automatic methods to detect multiple sclerosis lesions in

[1] M.Sc. dissertation

the brain MR images [5]. Those and other related works in the literature generally propose methods to automatically identify WMH 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.

The WMH etiology varies according to age, but ischemic and demyelinating are the more frequently observed. Demyelinating lesions are detected in patients with multiple sclerosis [6], while the ischemic ones are found in ischemic stroke patients [7]. It is also possible to observe lesions with different etiology in the same patient.

Main goal: This master dissertation proposes an approach 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 WMH based on their etiology, called classification task. Texture analysis is a branch of image processing [8] that has been used in many medical images applications [9], such as tissue characterization [10] and segmentation of diffuse lesions of the brain's white matter [11]. Classification is one of the most important tasks in the machine learning field. In medical imaging, there are many works in 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 different classifiers, such as Support Vector Machine, Linear Discriminant Analysis, Optimum Path Forest and k-Nearst Neighboors, in order to compare their accuracy rates. We also performed experiments with attributes selection methods, such as Principal Component Analysis and the Decision Tree. The method was developed in Adessowiki [12], a collaborative environment for development and documentation of scientific computing algorithms.

II. Methodology

The proposed analysis of white matter hyperintensities receives as input manually segmented regions of interest (ROIs) and returns as output the corresponding class of each ROI. The proposed method was subdivided into four 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 in with the texture attributes were extracted from each segmented region of interest, followed by the attribute selection procedure (third step). The last step represented the classification procedure that comprised the WMH identification and the WMH classification tasks. This whole process is schematized in Fig. 2.

A. 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) at the Clinical Hospital of the Medical Science Faculty of UNICAMP. Regions of Interest (ROIs) were manually selected and annotated by an expert. In total, 76 ROIs of normal white

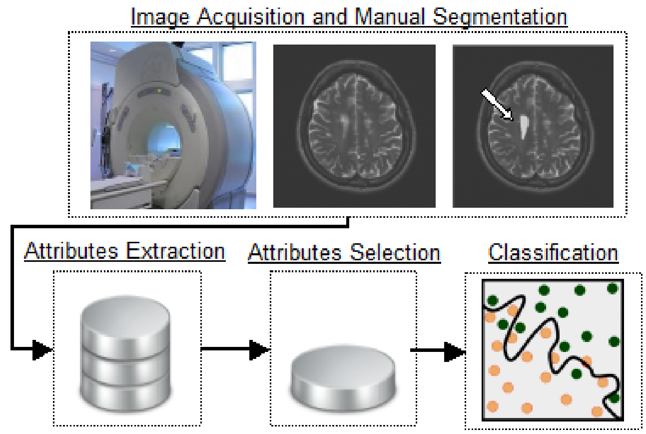

Fig. 2. Proposed method overview: image acquisition and manual segmentation, followed by the texture analysis and attributes selection, finalized by the WMH identification and classification.

matter, 64 ROIs of WMH with ischemic etiology and 143 ROIs representing WMH with demyelinating etiology were selected. Fig. 3 presents some ROIs examples showing that they usually have different sizes and shapes and contain only one type of tissue.

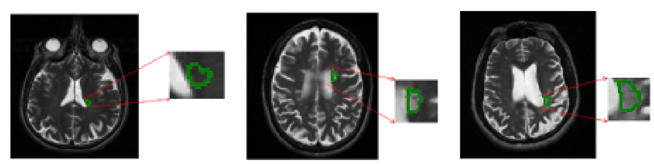

Fig. 3. Image samples: normal white matter ROI (left), WMH with ischemic etiology ROI(middle), and WMH with demyelinating etiology ROI (right)

B. Attributes Extraction

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 different patterns presented in the analyzed region [13]. 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 the following texture analysis approaches:

- Statistical approach based on the gray level histogram: extraction of metrics based on the gray level distribution in the region of interest, such as mean, variance, skewness and kurtosis, among others.
- Gray Level Co-occurrence Matrices (GLCM) approach: the co-occurrence matrix [8] analyze the occurrence of pairs of pixels with gray level i and j in a image given a specific offset and orientation between them. We

computed the co-occurrence matrix in different distances (1, 2, 3, 4 e 5) and in different orientations (0^0, 45^0, 90^0 e 135^0).
- The Run Length Matrix (CC) approach: the run length matrix [14] analyze the frequency in which a specific number of pixels with the same gray level occurs consecutively in a determined direction. It was computed in different orientation (0^0, 45^0, 90^0 e 135^0).
- Statistical approach based on the gradient: extraction of metrics based on the gray level distribution of the region of interest gradient [15].
- Autoregressive model approach: The autoregressive model [16] assumes a local interaction between pixels in an image, so the pixel intensity can be represented as a weighted sum of its neighbors intensity. The parameters model θ_1, θ_2, θ_3, θ_4 and σ are extracted through the numeric solution of its equations.
- Haar Wavelet decomposition approach: different from co-occurrence matrices and run length matrices, haar wavelet [17] possess the sensibility to identify rougher texture alterations. The extracted metrics represent the energy of each sub-image generated through the wavelet decomposition. We use two decomposition levels.

A total of 87 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[2], a computer program for calculation of texture parameters in digitized images.

C. Attributes Selection

The methods of attributes selection reduce the size of the database through the removal of irrelevant or redundant attributes in order to find a minimum set of attributes that represent the original one. This procedure makes the classification task easier and straightforward [18]. We applied in this work two different methods of attributes selection: principal component analysis (PCA) and the decision tree algorithm.

PCA proposed in 1901 by Karl Pearson [19], is a mathematical procedure to reduce the data set by discarding redundant information. The result is a lower number of non-correlated attributes, named principal components. This compact representation makes the following classification task faster [20].

On the other hand, the decision tree algorithm [21] was originally intended for classification, but nowadays is largely used as an attributes selection method. The main goal of this technique is to generate a tree structure that summarizes relevant information of the input data, making possible its visualization and interpretation. Each internal node in the tree structure represents an attribute test, and its possible results are indicated in the edges. Finally, the external nodes present the final prediction. After the decision tree construction, it is possible to choose the most discriminative attributes.

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

D. Classification Procedure

The final step of the proposed methodology aims to distinguish the previous segmented ROIs between normal and non-normal white matter (identification task), and to distinguish ROIs containing WMH based on their etiology: demyelinating or ischemic (classification task). In order to accomplish these tasks, the classifiers SVM, OPF, LDA and kNN 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 hyper planes in a high dimensional space that optimally separates the data into two categories [22]. The Optimum Path Forest (OPF) [23] 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 Discrinant Analysis (LDA). LDA is parametric and statistical method that can be used to attributes selection, so as to the classification procedure. Also, we tried to execute the classification task by using the k-Nearest Neighbor classifier (kNN). The kNN decision rule assigns to an unclassified sample point the most frequent label of its k nearest previously classified points [24]. The 1NN classifier, kNN classifier using $k = 1$, 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 [25].

We executed the WMH identification and the WMH classification tasks using SVM, OPF, LDA and kNN 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.

III. Experiments and Results

The experiments were conducted in order to measure the representative capacity of the texture attributes, how effective are the attributes selection methods, and also the classifiers accuracy while performing different tasks. The first task comprises the WMH identification (Id), that aims to distinguish ROIs between normal and non-normal white matter tissue. The second one represents the WMH classification (Cl) that differentiate between ischemic and demyelinating lesions. The final task comprehends both tasks, in with the WMH identification and WMH classification (IdCl) are performed simultaneously, designing a classifier to distinguish between 3 classes: normal tissue, WMH with ischemic etiology and WMH with demyelinating etiology.

These proposed tasks were accomplished by SVM, kNN, LDA and OPF using different parameters configuration. For SVM, we tested both linear and rbf kernels [26], and the parameters were selected through a grid-search technique. We also simulated different configurations of OPF by changing the distance metric (euclidean or manhattan), and kNN by varying k values ($k = 1$, $k = 3$ and $k = 5$). Finally, we performed experiments with different attributes selection techniques, such as PCA and decision tree in order to find the best set of attributes to distinguish different classes.

Among all these possible combinations of techniques and parameters configuration, Table I shows the achieved results for the best combination of techniques to accomplish each one of the proposed tasks. The classifier SVM with linear kernel ($C = 10$), without any attribute selection method presented the best accuracy rate in task Id. The classifier LDA achieved in this task an accuracy rate of 99% combined with PCA, while kNN presented an accuracy of 98.61% using $k = 1$ and combined with the decision tree method. Finally, OPF combined with decision tree achieved the lowest accuracy rate in this task: 98.28%.

The best classifier for task Cl was LDA combined with PCA, that presented an accuracy rate of about 87%. The SVM classifier achieved a similar accuracy rate (86.76%) using rbf kernel, with parameter $C = 100$ and $\gamma = 0.1$. Identical results were reached by OPF with euclidian distance and kNN using $k = 3$, both combined with PCA.

At least, the classifier SVM with rbf kernel, $C = 10$ and $\gamma = 0.1$, without attributes selection procedure, achieved an accuracy rate of 91.70% when accomplishing the IdCl task. LDA presented an accuracy of 89.60%, while kNN with $k = 3$ reached an accuracy rate of 88.42%, both combined with PCA. Once more, OPF presented the lowest accuracy rate (87.92%) by using the manhattan distance, when applying the decision tree for attribute selection.

TABLE I
BEST ACCURACY RATES ACHIEVED FOR ID, CL AND IDCL TASKS.

Tarefa	SVM	kNN	OPF	LDA
Id	**99.35±0.02**	98.61±0.02	98.28±0.01	99.00±0.01
Cl	86.76±0.04	83.65±0.02	83.65±0.04	**86.91±0.06**
IdCl	**91.70±0.04**	88.42±0.04	87.92±0.04	89.60±0.04

In addition, we also performed experiments in order to deeper analyze the texture attributes extracted from regions of interest. Fig. 4, Fig. 5 and Fig. 6 present graphics containing the texture attributes in decreasing order of importance degree while performing the tasks Id, Cl and IdCl, respectively (the most discriminating attributes present the highest degrees of importance). It is relevant to notice that, for visualization purpose, each graphic shows only 30 attributes, while our entire set of attributes present 87 texture attributes.

It is possible to verify through the analysis of these graphics that the texture attributes extracted from co-occurrence matrix and from histogram are the most frequent attributes groups in all proposed tasks, stressing its relevance in the white matter hyperintensity identification and classification.

IV. Discussion

The combination of image processing and pattern recognition techniques achieved high accuracy rate in the Id task, indicating that the texture attributes extracted from ROIs are representative, making easier to accomplish the following classification step. The classifier with worst result in this task

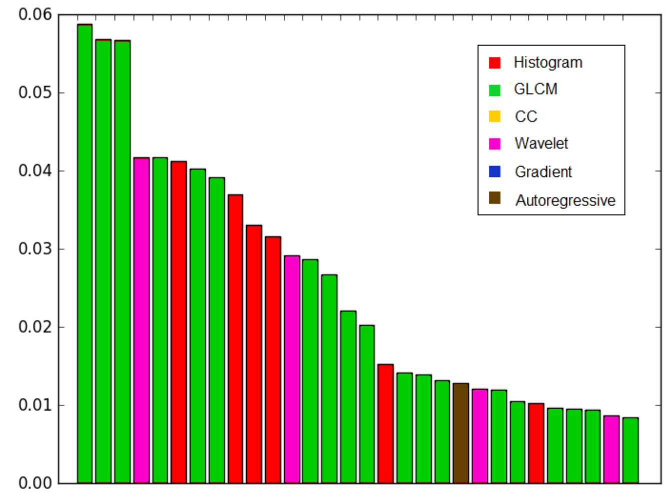

Fig. 4. Representation of the attributes importance computed by the decision tree algorithm while performing in Id task (in decreasing order).

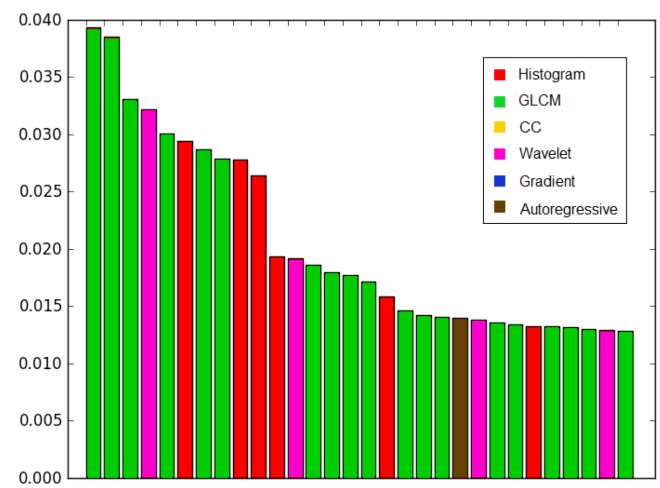

Fig. 5. Representation of the attributes importance computed by the decision tree algorithm while performing in Cl task (in decreasing order).

presented an accuracy rate of 98.28%, about only 1% lower than the accuracy rate obtained by the best classifier. Thus, in a real system of lesion identification based on texture attributes, any classifier (SVM, LDA, kNN or OPF) can be suggested, since all of them achieved high accuracy rates. In this case, the choice of which classification method should be used must consider other criteria, such as implementation complexity, processing time, among others.

The Cl task, on the other hand, even presenting an acceptable accuracy rate, present the lowest results among the proposed tasks, 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. The difference in the accuracy rate between the best and the worst classifier was about 3%, so the most suitable method for this task is LCA combined with PCA. The

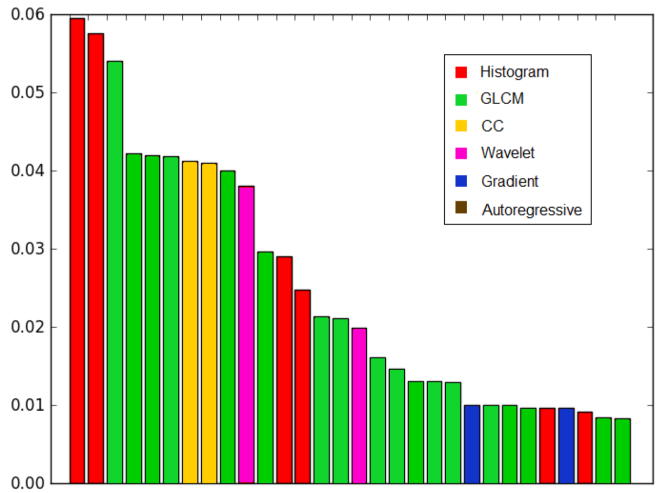

Fig. 6. Representation of the attributes importance computed by the decision tree algorithm while performing in IdCl task (in decreasing order).

SVM classifier achieved similar accuracy rate (less than 0.2% lower than LDA accuracy rate), and so as LDA, posses a wide variety of available implementation and documentation in the literature, and it is so indicated as LDA to accomplish Cl task.

The results also confirmed that the OPF and 1NN classifiers presented similar accuracy rates, as previously commented, since they present many conceptual similarities. In the task IdCl, for example, OPF presented an accuracy rate of 84.10%, while 1NN achieved 84.46% when using the euclidean distance, both combined with PCA. By using the manhattan distance, OPF accuracy rate increased about 3% (achieving 86.92%), indicating that the use of this distance generate a more discriminative classifier.

Finally, there is no overall better attribute selection method, since each task presented the best accuracy rate using a different attribute selection method or even no attribute selection at all. We can highlight, on the other hand, SVM and LDA classifiers, since they presented the best accuracy rates in both WMH identification and classification. Besides, 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.

V. Conclusion and Perspectives

The experiments have shown that the combination of texture analysis and kNN, OPF, LDA and SVM classifiers is suitable techniques for identification and classification tasks. 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. It was 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.

Among the compared classifiers, we can highlight SVM and LDA for presenting the best accuracy rates in the execution of all proposed tasks. Besides, through the degree of importance analysis, we can conclude that the texture attributes extracted from the co-occurrence matrix and from the histogram area are the most relevant ones in the identification and classification of WMH.

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. Besides, we are also planning to increase the image database in order to validate the method and to analyze its robustness. Finally, we also intend to eliminate the manual segmentation step by developing a semi-automatic method for WMH segmentation.

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