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# Use of Fuzzy Techniques for Detection of Multiple Sclerosis Small Lesions

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**Abstract**

This work shows an application of algorithms in which fuzzy techniques are used. It is focused on the automation of image analysis for use with a non-invasive technique, as magnetic resonance, in multiple sclerosis patients, and specifically in detection of the smallest lesions. The typical uncertainty in the definition of these lesions lead us to consider that a fuzzy approach is a good solution to the problem.

The design of the algorithm is based on the definition of a rule set, which enable feature extraction and data analysis. The fuzzification process is solved by means of probability density functions. In this way we obtain OWA operators that achieve a high degree of detection in these lesions.

The proposed design resolves the problem of false detections by the use of various filters implemented from new rules.

**Keywords:** computer vision, fuzzy techniques, magnetic resonance, multiple sclerosis.

## 1 Introduction

Multiple sclerosis (MS) is a disease of the central nervous system characterised by destruction of the myelin that encases the axons. This demyelinating process results in an inhibition of neural transmission and causes the appearance of several clinical symptoms, such as motor and sensory disturbances, paralysis or visual alterations [1,5].

Magnetic resonance imaging (MRI), a clinical diagnostic technique providing excellent soft tissue differentiation, is generally used to confirm the diagnosis of MS [2,8]. In fact, in the early 80's, the period in which MR came into clinical use, diagnosis of MS was one of the first fields in which MRI was applied.

In a MRI brain study, the disease is manifested by alterations in the normal intensity of the regions where demyelination is produced. These changes are observed as a series of plaques or lesions, generally of small size and elliptical shape. The lesions are usually located on the so-called white matter and, predominantly, surrounding the ventricular region.

Detection of these lesions is important to confirm the diagnosis of MS and, in follow-up studies, to evaluate the course of the disease and the response to treatment. At the present time there is no therapy that modifies long-term outcome, and numerous clinical trials are directed toward finding drugs to fight against the disease. Since the early 90's, the relevance of MRI in clinical trials has motivated a great deal of effort toward developing methods for segmentation of the affected region, with the aim of measuring the lesion load in patients.

The process of lesion detection is difficult because of the great deal of uncertainty regarding definition of the lesion, a fact that affects the final quantification considerably [2]. Currently, only semi-automated segmentation methods [5,9,10] are in use, although ideally automated methods avoid inter-observer errors and achieve better comparability of results [2,4]. Moreover, since these examinations imply analysis of several images, automation also facilitates evaluation of the small differences that might exist between two consecutive studies.

The degree of uncertainty observed depends, to a great part, on the features of each image and on factors such as noise and the effect of magnetic field non-homogeneity over the image, elements that are particularly critical in smaller lesions, which often have extremely vague contours.

The aforementioned considerations regarding MS lesions have prompted us to propose implementation of a rule-based algorithm departing from the methodology used by the neuroradiologists for small lesion detection, in which a fuzzy analysis of the information has been introduced.

## 2 Structure of the algorithm

Density and T2 weighted MR brain images were obtained with a 1.5 T Magnetom instrument (Siemens, Germany) using an $SE_{2200/12-80}$ sequence. We performed 5 mm slices at 1 mm distance with a field of view of 250 mm and a 192x256 matrix. Contrast was injected before data acquisition.

The methodology that the radiologists use to diagnose MS from the acquired images is based on the observation of a hyperintensity in relation to the surroundings. This hyperintensity is associated with the process of demyelination of the axons, and is visualised as an increase in grey level intensity with respect to the surroundings in both the D and T2 weighted images. The differentiation of actual lesions from other areas with a similar appearance lead us to a series of rules to characterise the hyperintensity observed in the lesions:

- Location only on encephalic parenchyma.
- Hyperintense signal for both weighted images (T2 and D).

- Lesions are visualised better on T2 weighted images, however several regions without lesions may also present hyperintense signals on this image. This occurs to a lower degree on the D weighted images.
- Typically elliptical shape, although a proximity to other lesions may produce overlapping effects. Size is usually under 9 pixels at the largest axis and minimum number of pixels comprising a lesion is 3 or 4.
- A hyperintensity located on the border between the ventricles and the parenchyma is considered to be a lesion only when it shows a very high intensity variation in relation to its surroundings (less frequent case) or when it describes a perpendicular path to the contour of the ventricle.

These rules can be applied to any lesion, regardless of size. Small lesions, which are the aim of this study, are defined as lesions that can be included in a 5x5 window.

The algorithm for lesion detection based on the aforementioned rules consists of the following sections:

- Normalisation of the grey level values of the acquired images.
- Feature extraction and evaluation.
- Fuzzification.
- Rule-based data analysis.
- Defuzzification.
- Filtering.

The nineteen images per study acquired with the 1.5 T equipment, using an $SE_{2200/12-80}$ sequence with the aforementioned sequence parameters were analysed on an SGI Indigo2 XZ work station. Normalisation of the values obtained consisted of a non-linear histogram transformation process, assigning the value 0 to the first 16,000 pixels with lowest values, and 242 to the 100 pixels with highest values; the remaining pixels were linearly distributed within this new interval according to their grey levels.

## 3 Feature Extraction

Three groups of features are considered, based on the grey level of the pixels within the lesion, and that of the pixels outside and surrounding the lesion. In addition, relative values are evaluated from the intensity values of these pixels.

The feature extraction process was done on 7 patients. The lesions observed were marked by several radiologists, and from these, only the lesions included within a 5x5 window were selected. For feature extraction, a 7x7 window is superimposed over the small lesion and values are acquired only when none of the pixels

comprising the lesion occupy the row or columns outside the 5x5 centred window. Thus, two different kind of values are acquired: those located clearly within the lesion and those located outside and surrounding the lesion (halo). The acquisition process is performed for the D and T2 weighted images, and since T2 weighted images show the lesions more clearly, it allows to obtain more values from them.

The presence of a hyperintensity in a certain region is determined in the feature's space according to the following rules:

1. A region shows greater hyperintensity when the grey level value of its pixels is high enough.
2. A region shows greater hyperintensity when there are a sufficient number of radii in which the difference between the value of the central pixel and the values of the radial pixels is relatively high, although clearly lower enough in relation to the central pixel value.
3. A region shows greater hyperintensity when there are enough radii in which the central pixel value is clearly higher enough in relation to the radial pixel values.

In the implementation of these rules, the following groups of features are considered:

1. Grey level value.
2. Ratio of the difference between the value of the lesion and the value of the outside halo, and the lesion value ((lesion value - halo value)/lesion value).
3. Ratio of the lesion and outside halo values (lesion value/halo value).

To evaluate these features, a 7x7 window is centred over each pixel. The first feature corresponds to the grey level value of the central pixel. The second and third groups are evaluated considering each of the eight-way radii, selecting the three possible values for each radius, since is not known *a priori* which of the three pixels belongs to the halo.

# 4 Fuzzification

A fuzzy set is associated with each of these groups of features, obtaining 6 fuzzy sets ($fs_{1T2}, fs_{2T2}, fs_{3T2}, fs_{1D}, fs_{2D}$, and $fs_{3D}$). The membership degree of each pixel to these sets is defined in the way introduced by Montseny-Sobrevilla [6], using probability density functions obtained for each feature from the *design set*. Fuzzification, based on these models, permits a transformation of the feature space to a function having values within the unit interval. This is applied to the three groups of features considered and to the two types of weighted images (D and T2), obtaining six functions.

The resulting values for the three groups of features and the two weighted images are fuzzified in accordance with the functions defined above. In this way,

the membership degree of the central pixel to each one of the three fuzzy sets was determined. The membership degree for the second and third features was obtained in the following way:

- The three values for each radius are aggregated by using the OWA operator: [1,0,0].
- The eight values obtained in the previous step, corresponding to the eight radii, are aggregated by using the OWA operator: [0,0,0,1,0,0,0,0].

## 5 Rule-based data analysis

To analyse the data, we use the rule introduced in section 2: 'lesions show hyperintensity on both weighted images (T2 and D)' and the definition of small lesion, which lead us to the following implication rules:

- The greater the membership degree of a pixel (i,j) to $fs_{1D}, fs_{2D}$ and $fs_{3D}$, the greater is its membership to $fs_D$.
- The greater the membership degree of a pixel (i,j) to $fs_{1T2}, fs_{2T2}$ and $fs_{3T2}$, the greater is its membership to $fs_{T2}$.
- The greater the membership degree of a pixel (i,j) to $fs_D$ and $fs_{T2}$ (fuzzy sets associated with weighted images, the greater is its membership to $fs_H$ (fuzzy set associated with a hyperintensity).

The membership degree of each pixel to the new fuzzy sets ($fs_D$, $fs_{T2}$ and $fs_H$) is obtained using the following OWA operators:

0,1,0 for $fs_D$.

0,1,0 for $fs_{T2}$.

0,1 for $fs_H$.

## 6 Defuzzification

The defuzzification process yields the groups of pixels that may correspond to small lesions. This is achieved by means of an $\alpha$-cut ($\alpha$=0.5) over the fuzzy set $fs_H$.

When this process is applied, a set of groups of pixels is obtained in the analysed area. Some of the groups detected corresponded to non-small lesions (according to the definition) and some to regions without lesions. These two groups are considered to be false detections.

# 7 Filtering

The procedure for eliminating false detections is based on a new set of rules, which consider aspects of these lesions that differentiate them from true small lesions, and the definition of hyperintensity (section 2). So, the following rules are established to define true small lesions:

- Small lesions show a minimum number of pixels.
- Small lesions do not present more than 25 pixels.
- Location only on the encephalic parenchyma.
  - Lesions cannot be located on the division between the two hemispheres of the brain.
  - Lesions cannot be located on the subarachnoid spaces of the convexity of the hemispheres.
- If the hyperintense area is located on the border between the ventricles and the parenchyma, it is considered to be a lesion when it shows a very high intensity variation in relation to its environment (less usual situation) or when it describes a perpendicular path to the ventricle contour.

# 8 Results

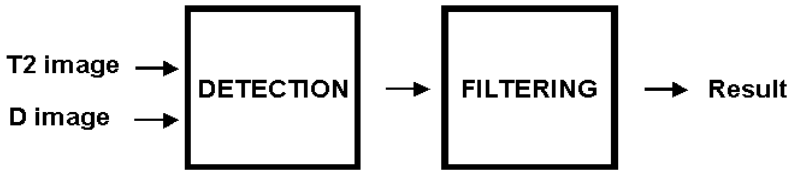


Figure 1: Result obtention process

To analyse the results, the algorithm is divided into two stages (figure 1), the first including points 1 to 5 described in section 2. The algorithm was applied over 63 images with the following results:

- True detections: 91.43%
- False detections (mean per image): 203.66

It was observed that:

- The majority of small lesions are detected.
- The number of false detections has to be reduced.

To eliminate false detections, we apply a filtering process based on size that included:

A. Filter to select groups between 3 and 25 pixels.

B. Filter to select groups between 4 and 25 pixels.

The results are shown table 1.

| | Detection | Filter A | Filter B |
|---|---|---|---|
| True detections | 91.43% | 82.86 % | 62.86 % |
| False detections (mean per image) | 203.66 | 78.75 | 59.95 |

Table 1: Detection levels according to size filtering of groups of pixels.

Another filtering process based on location is then applied:

C. Filter to eliminate detections located on the division between hemispheres.

D. Filter to eliminate detections located on the subarachnoid space of the convexity of hemispheres.

Results are depicted in table 2.

| | Detection | Filter A | Filter A+C+D |
|---|---|---|---|
| True detections | 91.43 % | 82.86% | 80 % |
| False detections (mean per image) | 203.66 | 78.75 | 20.35 |

Table 2: Detection levels according to size and location filtering.

Images 2 to 5 show the process for obtaining the results from analysing the two images (D and T2) in the two filtering situations.

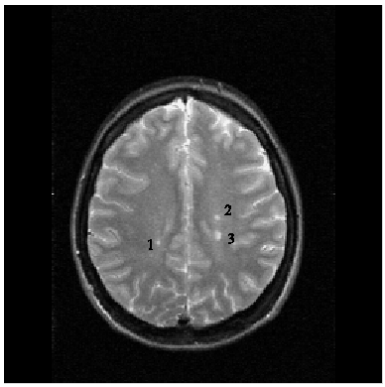


Figure 2: T2 weighted image.

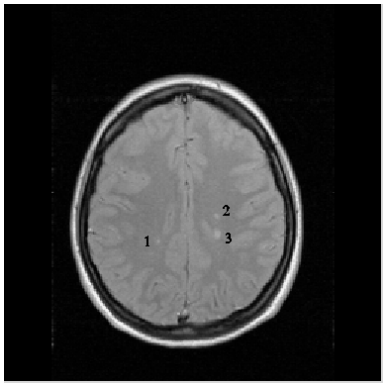


Figure 3: Density weighted image

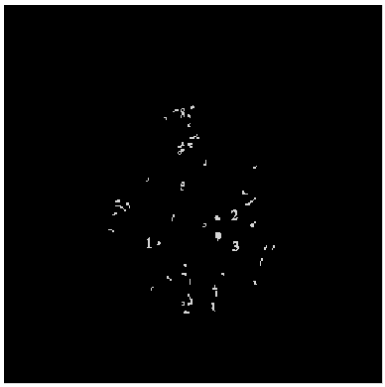

Figure 4: Result applying detection and A filter

Figure 5: Results to apply detection and A, C and D filters

## 9 Conclusions

This study presents an algorithm designed to detect multiple sclerosis small brain lesions on MR images. Since no shape constraints have been imposed, lesions of larger size may also be detected with this method.

The minimum size threshold for detection was established at 3 pixels. At lower limits true detection was not improved and the number of false detections increased considerably.

The application of fuzzy techniques has resulted in a formalisation of the hyperintensity to permit the detection of small lesions, and has facilitated the implementation of the rules used by neuroradiologists for this purpose.

Although the number of false detections remains excessive, we have observed that the implementation of new rules based on location can eliminate them.

At the present time our efforts to improve the algorithm are focused on the following points:

- Improving detection capability by optimising the use of the probability density function.
- Increasing filtering levels, departing from maximum segmentation of the region of interest.
- Implementation of validation functions to improve detection.

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