Artificial Neural Network (ANN) Morphological Classification of Magnetic Resonance Imaging in Multiple Sclerosis

Alessia Bramanti[1,2], Lilla Bonanno[2], Placido Bramanti[2], and Pietro Lanzafame[2]

[1] Faculty of Engineering, University of Messina
[2] IRCCS Centro Neurolesi "Bonino-Pulejo"
alessia.bramanti@gmail.com

Abstract. Multiple Sclerosis (MS) is an autoimmune condition in which the immune system attacks the Central Nervous System. Magnetic Resonance Imaging (MRI) is today a crucial tool for diagnosis of MS by allowing in-vivo detection of lesions. New lesions may represent new inflammation; they may increase in size during acute phase to contract later while the disease severity is reduced. To monitor evolution in time of lesions and to correlate this to MS phases, we focused on the application of Artificial Neural Network (ANN) based classification of MS lesions. An euclidean distance histogram, representing the distribution of edge inter-pixel distances, is used as input. In this work, we have extended the study already published, increasing to 21 the number of images. We can observe that the percentage of correct results on 21 images (93.81%) increased if compared to the study performed on 13 images (92.31%). This methodology could be used to monitor evolution in time of lesions of each patient and to correlate this to MS phases (i.e. to know if the lesions change their form).

Keywords: Multiple Sclerosis, Magnetic Resonance Imaging, Artificial Neural Network based classification, Euclidean Distance Histogram.

1 Introduction

Multiple Sclerosis (MS) is an autoimmune condition in which the immune system attacks the Central Nervous System (CNS) [1].

Magnetic Resonance Imaging (MRI) has become the most sensitive paraclinical test in diagnosis, assessment of disease evolution and treatment of the effects in MS. MRI is used as a prognostic tool at the first presentation of symptoms, suspicious of brain demyelination. Multiple hyperintense lesions on T2-weighted sequences are the characteristic MR appearance of MS. The majority of lesions are small, although, can occasionally measure several centimeters in diameter. MS lesions are usually small with intermediate high signal intensity with less severe degree of inflammation [2]. MS lesions tend to have an ovoid configuration with the major axis perpendicular to the ventricular borders (Dawson's fingers) (fig. 1).

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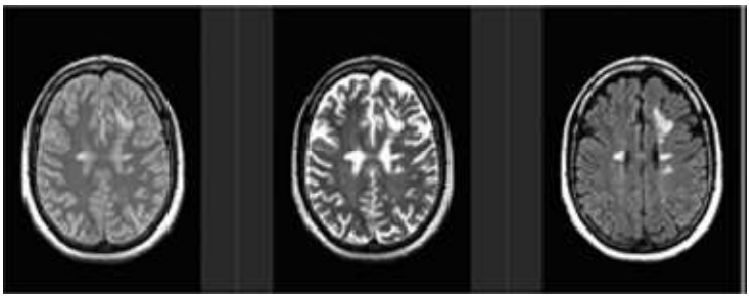


Fig. 1. Axial proton density (PD), T2-weighted and Fluid Attenuated Inversion Recovery (FLAIR) images of a patient with MS demonstrate multiple hyperintense lesions with periventricular predominance

Most lesions, especially in the early stages of the disease, are evident on conventional MRI but diffuse irregular hyperintensities have also been demonstrated in the later stages of the disease. These areas with poorly defined borders, are usually seen around the ventricles and called dirty appearing white matter (DAWM).

2 Materials and Methods

The images have been acquired at IRCCS Centro Neurolesi ”Bonino Pulejo” of Messina in DICOM format and transformed in png format. The cropped images, containing only a lesion, were used. These smaller images are the input of the algorithm (example in fig. 2). We used MRI images from the MS patients which were stored in a database to be read by the algorithm automatically and sequentially [3]. A preliminary study was published in Communication to SIMAI Congress, “Artificial Neural Network (ANN) Morphological Classification by Euclidean Distance Histograms for Prognostic Evaluation of Magnetic Resonance Imaging in Multiple Sclerosis”, when we considered 13 image [4].

In this work, we have extended the work already published, increasing to 21 the number of images.

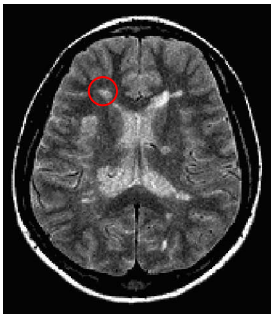


Fig. 2. Original image

We used a Multilayer Perceptron network (fig. 3). This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents [5].

We considered multi-layer architectures because units are often numbered by layer, instead of following a global numbering.

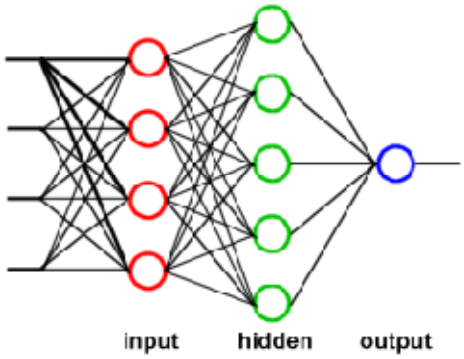


Fig. 3. Multilayer Perceptron

For the construction of training set, it must be obtained the contour of the lesion from the corresponding cropped image, through the following [6]:

- applying a thresholding global operation obtaining a segmented binary image;
- realizing uniform the internal of the lesion;
- applying to the obtained image the Laplacian operator, which can be implemented as the filter

$$H = \begin{vmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{vmatrix}$$

This formulation of Laplacian operator is called the 4-neighbours and allows us to obtain as a result the contour of the lesion [7] (fig. 4).

Once obtained the contour, we can calculate found edge inter-pixel distances and construct a histogram have been normalized to ten values which represents the number of occurrences of distances (y axis in the histogram) that have a certain value (axis x in the histogram) (fig. 5).

(a) (b) (c)

Fig. 4. (a) Segmented binary image; (b) Binary image after morphological operation; (c) Contour of lesion

The histogram have been normalized to ten values by the following formula (1):

$$dI = \frac{D_e \cdot d_{i_{max}}}{d_{max}} \tag{1}$$

where $d_{i_{max}} = 10$ is the values number of the normalized histogram, dmax = 35 is the maximum distance of the relative contour, D_e is the euclidean distance and dI is the correspondent index to the calculate distance.

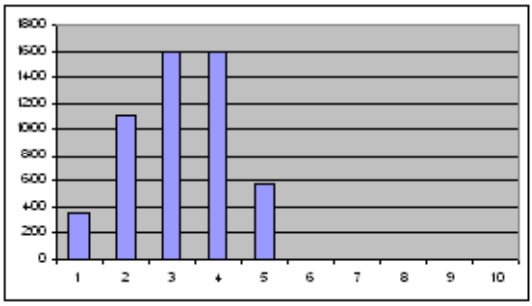


Fig. 5. Histogram normalize to ten values

The examples that the administrator must provide are the values, normalized between 0 and 1, of the built histogram. All examples chosen for the training phase of the network are included in the training set, which is a file of "training". For each lesion the euclidean distance histogram of its contour is calculated, by the following formula (2).

$$D_e(p,q) = \sqrt{[(x-s)^2 + (y-t)^2]} \tag{2}$$

where D_e is the euclidean distance, p(x, y) and q(s, t) are two pixels of the contour. These values are stored on a file. Each row represents data of a contour and it is composed by thirteen value: in the first ten columns there are values of the obtained histogram and in the last three columns values that the network should produce. Since we consider three classes of contours, that of type *irregular*, *rounded* and *elongated*, these values are respectively 1 0 0 for values belonging to the first class (*irregular contours*), 0 1 0 for second class (*rounded contours*) and 0 0 1 for the third class (*elongated contours*).

2.1 Contour Recognition

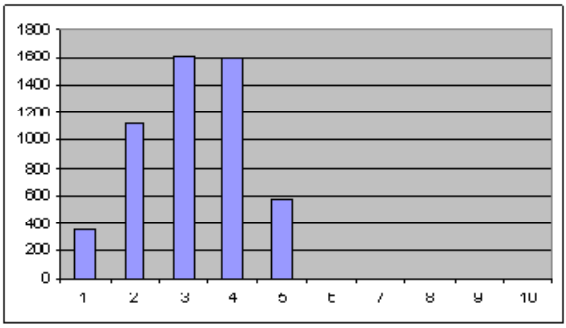
Giving the neuronal network, an image containing a lesion of MS as input, produces output results. Through the study of output values, depending on how the neural network were trained, it can be established if the examined lesion belongs to a particular class. For example, providing to the network the image of a lesion, it can be got as output values [0.00, 0.26, 8.91].

By establishing a threshold this vector can be rounded to [0, 0, 1]. This means that the network has recognized the lesion, classifying it as lengthened contour.

3 Results

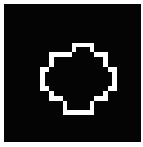
The neural network was trained using the data of seven pictures for each class of contour, while for verification have used data of seven images for the classes *elongated*, *rounded* and *irregular*. The figure (fig. 6- 8) shows some examples of training data.

(a)

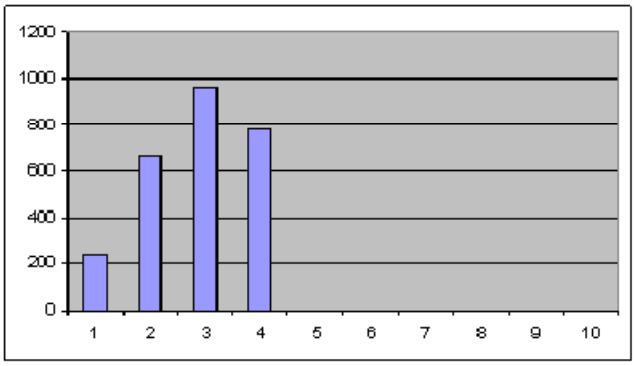


(b)

Fig. 6. (a) Irregular contour; (b) Normalised euclidean distances histogram

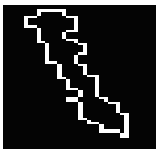


(a)

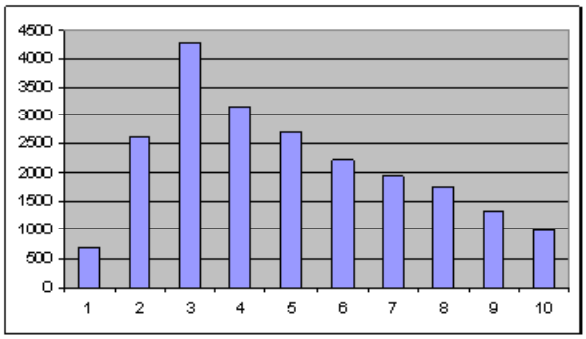


(b)

Fig. 7. (a) Rounded contour; (b) Normalised euclidean distances histogram



(a)



(b)

Fig. 8. (a) Elongated contour; (b) Normalised euclidean distances histogram

From the table 1, we see that the results are correct at 93.81% and positive falses are 6.19%.

Table 1. The results obtained

Image	Membership class	Output	Membership class output
n.1	Elongated	0.00 – 0.26 – 0.91	Elongated
n.2	Elongated	0.00 – 0.05 – 1.00	Elongated
n.3	Elongated	0.00 – 0.05 – 1.00	Elongated
n.4	Elongated	0.00 – 0.33 – 0.90	Elongated
n.5	Elongated	0.00 – 0.28– 0.96	Elongated
n.6	Elongated	0.00 – 0.30 – 1.00	Elongated
n.7	Elongated	0.00 – 0.33 – 0.90	Elongated
n.8	Rounded	0.20 – 0.12 – 0.92	Uncertain
n.9	Rounded	0.17 – 0.71 – 0.05	Rounded
n.10	Rounded	0.21 – 0.74 – 0.03	Rounded
n.11	Rounded	0.22 – 0.74 – 0.03	Rounded
n.12	Rounded	0.18 – 0.70 – 0.04	Rounded
n.13	Rounded	0.20 – 0.74 – 0.03	Rounded
n.14	Rounded	0.19 – 0.75 – 0.05	Rounded

Table 2. (*continued*)

n.15	Irregular	0.75 – 0.38 – 0.00	Irregular
n.16	Irregular	0.96 – 0.00 – 0.25	Irregular
n.17	Irregular	0.94 – 0.00 – 0.35	Irregular
n.18	Irregular	0.73 – 0.40 – 0.01	Irregular
n.19	Irregular	0.85 – 0.00 – 0.19	Irregular
n.20	Irregular	0.77 – 0.00 – 0.25	Irregular
n.21	Irregular	0.90 – 0.30 – 0.21	Irregular

4 Conclusions

The tests conducted during the verification of the classification algorithm by neural network have produced positive results in all cases: the neural network is capable to distinguish the different contours analysed, highlighting their class membership. MS lesions obtained by MRI images are simply an example of a possible application. In this work, we have extended the study already published, increasing to 21 the number of images. We can observe that the percentage of correct results on 21 images (93.81%) increased if compared to the study performed on 13 images (92.31%).

The set of made checks showed that the application meets the targets proposed and how it could be a useful support for the neurologist. This methodology could be used to monitor evolution in time of lesions of each patient and to correlate this to MS phases (i.e. to know if the lesions change their form).

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