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Artificial Neural Network (ANN) Morphological Classification by Euclidean Distance Histograms for Prognostic Evaluation of Magnetic Resonance Imaging in Multiple Sclerosis

Alessandro Celona[1], Pietro Lanzafame[1], Lilla Bonanno[1], Silvia Marino[1], Barbara Spanó[1], Giorgio Grasso[2], Luigia Puccio[3], Placido Bramanti[1]

[1] *IRCCS Centro Neurolesi "Bonino Pulejo"*
Via Provinciale Palermo Ctr. Casazza 98124 Messina, Italy
alessandro.celona@centroneurolesi.it, pietro.lanzafame@centroneurolesi.it, lilla.bonanno@centroneurolesi.it, silvia.marino@centroneurolesi.it, barbaraspano@yahoo.it, bramanti@centroneurolesi.it

[2] *Dipartimento di Fisica sez. Informatica*
Università degli Studi di Messina, Italy
ggrasso@informatica.unime.it

[3] *Dipartimento di Matematica, Facoltá di Scienze MM.FF.NN.*
Università degli Studi di Messina, Italy
gina@dipmat.unime.it

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. This work focuses on the application of Artificial Neural Network (ANN) based classification of MS lesions, to monitor evolution in time of lesions and to correlate this to MS phases. An euclidean distance histogram, representing the distribution of edge inter-pixel distances, is used as input. This technique gives a very promising recognition rate.

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) [4]. Magnetic Resonance Imaging (MRI) has become the most sensitive paraclinical test in

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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. MS lesions tend to have an ovoid configuration with the major axis perpendicular to the ventricular borders (Dawson's fingers) (fig. 1).

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. Task

To monitor evolution in time of lesions and to correlate this to MS phases, we focuse on the application of ANN-based classification of MS lesions. An euclidean distance histogram, representing the distribution of edge inter-pixel distances, is used as input. The main steps of this methodology are as follows:

- selection of MS images relating to several patients;
- classification of lesions through the use of a neural network;
- recognition of the type of lesion.

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).

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Fig. 2. Original image.

3. Neural network and neuron

A neural network is a computational system that simulate the biological neural systems, able to learn a criterion upon which to base its work, such as classification [5]. The basic unit of a neuronal network is the neuron, a threshold computational unit characterized by a series of inputs and a single output (fig. 3).

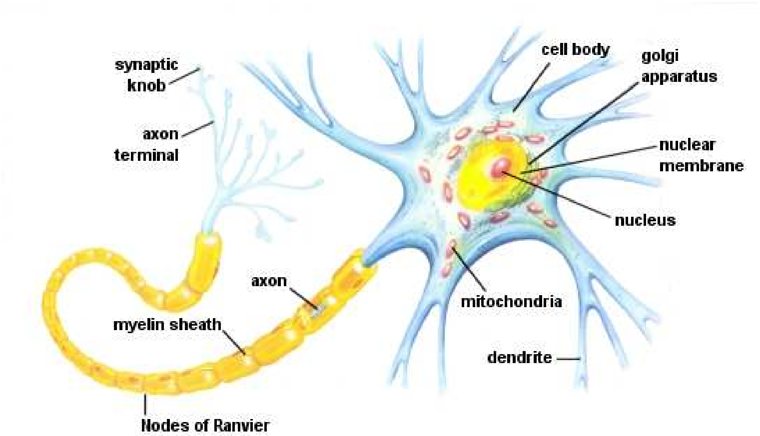

Fig. 3. Neural network.

3.1. *Multilayer Perceptron*

The network of neurons used is a Multilayer Perceptron (fig. 4), introduced by Frank Rosenblatt at Cornell University towards the end of 1959. This model consists of three levels of neurons:

- input layer;
- hidden layer;
- output layer.

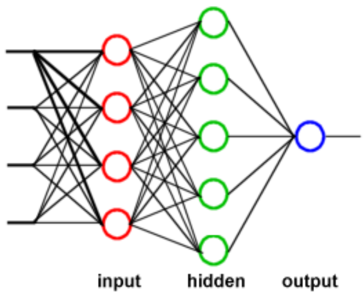

Fig. 4. Multilayer Perceptron.

Each unit in a level is linked to each one of the next level by a series of weighed connections. The network needs to learn in advance from a set of examples that the administrator chooses and organizes appropriately in a training set. These examples must be representative of the criterion that the network must learn.

3.2. *Construction of training set*

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

1. applying a thresholding global operation obtaining a segmented binary image;
2. realizing uniform the internal of the lesion;
3. 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 (fig. 5).

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)

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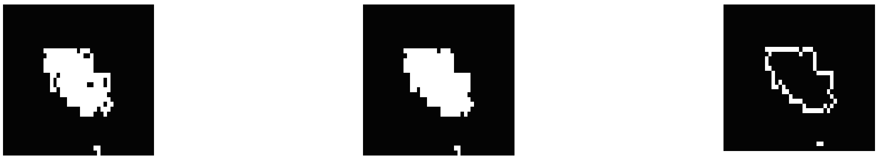


(a) (b) (c)

Fig. 5. (a) Segmented binary image; (b) Binary image after morphological operation; (c) Contour of lesion.

that have a certain value (axis x in the histogram) (fig. 6). 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, $d_{max} = 35$ is the maximum distance of the relative contour, D_e is the euclidean distance and dI is the correspondent index to the calculate distance.

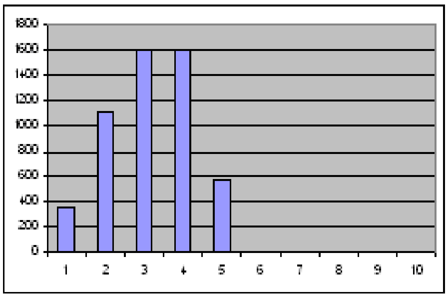


Fig. 6. Histogram normalize to ten values.

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 the its contour is calculated, by the following formula (2).

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

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 represent 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*).

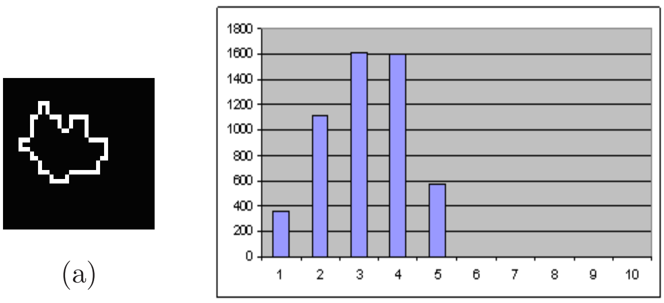
4. Contour Recognition

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.

5. Classification algorithm test

The neural network was trained using the data of seven pictures for each class of contour, while for verification have used data of four images for the classes *elongated* and *rounded* and five pictures for the class *irregular*. The figure (fig. 7 - 9) show some examples of training data.



(a)

(b)

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

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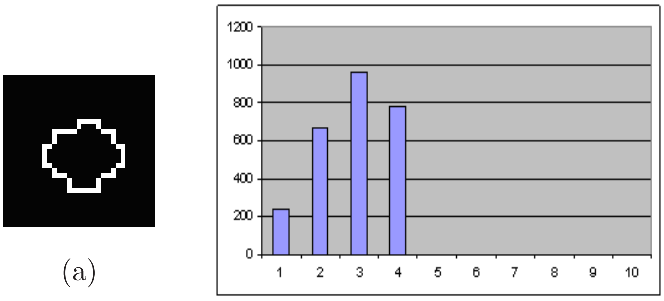
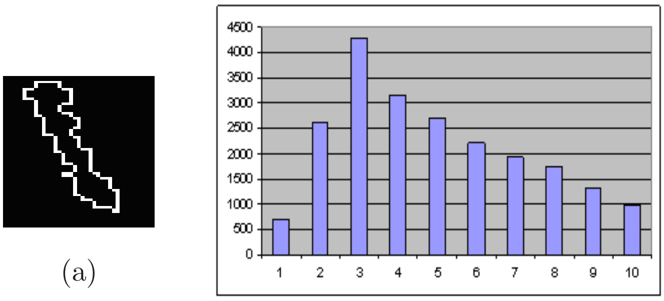


(a) (b)

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



(a) (b)

Fig. 9. (a) Elongated contour; (b) Normalised euclidean distances histogram.

In table (1) can be seen the obtained results.

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*
$n.5$	*Rounded*	0.20 – 0.65 – 0.07	*Uncertain*
$n.6$	*Rounded*	0.17 – 0.71 – 0.05	*Rounded*
$n.7$	*Rounded*	0.21 – 0.74 – 0.03	*Rounded*
$n.8$	*Rounded*	0.22 – 0.74 – 0.03	*Rounded*
$n.9$	*Irregular*	0.75 – 0.38 – 0.00	*Irregular*
$n.10$	*Irregular*	0.96 – 0.00 – 0.25	*Irregular*
$n.11$	*Irregular*	0.94 – 0.00 – 0.35	*Irregular*
$n.12$	*Irregular*	0.73 – 0.40 – 0.01	*Irregular*
$n.13$	*Irregular*	0.85 – 0.00 – 0.19	*Irregular*

From this table we see that the results are correct at 92.31% and positive falses are 7,69%.

6. Conclusions

The test of the network highlights that the network responds properly to the thirteen examples proposed. 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. The number of analyzed samples is not large enough to have any statistical significance, therefore, subsequently, it will be carried out tests with a wider data set. 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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