

Brain Tumor Image Segmentation Using Neural Networks

M. Martín-Landrove¹, R. Villalta¹

¹Centro de Resonancia Magnética, Facultad de Ciencias, Universidad Central de Venezuela, Caracas, DC, Venezuela

Introduction

Magnetic Resonance Spectroscopy (MRS) is a non-invasive tool that allows distinguishing brain malignant tumors from non-anaplastic tumors [1]. Metabolic maps can be obtained by the Chemical Shift Imaging (CSI) technique but they lack the spatial resolution necessary for therapy considerations [2,3]. Relaxometry studies have been used long ago for the assessment of tumors, being the T₂-map of a tissue often used as a basis for interpreting clinical images [4]. The combination of both techniques allows for the determination of nosologic maps with appropriate spatial resolution to establish, through segmentation, an accurate determination of Gross Tumor Volume or GTV commonly used in radiotherapy treatment planning. Neural networks have been extensively used for pattern recognition and classification. In the present work, it is proposed the use neural networks to obtain nosologic maps using information coming from MRS and Relaxometry.

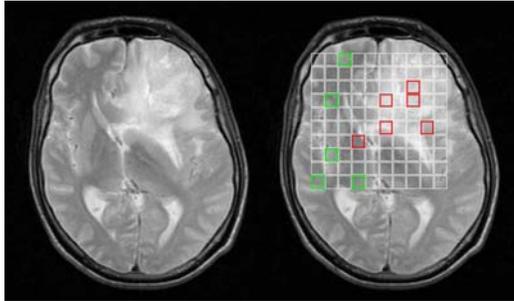


Figure 1. Left, T₂-weighted multi-echo image. Right, CSI grid used indicating voxels that correspond to pathologic tissue (red) and normal or unaffected tissue (green).

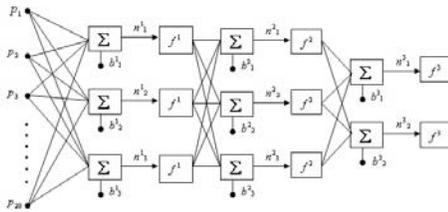


Figure 2. Neural network structure.

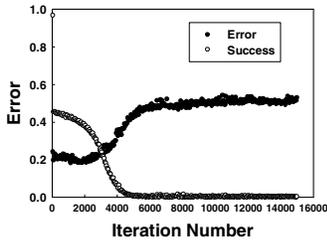


Figure 3. Learning plot for the neural network

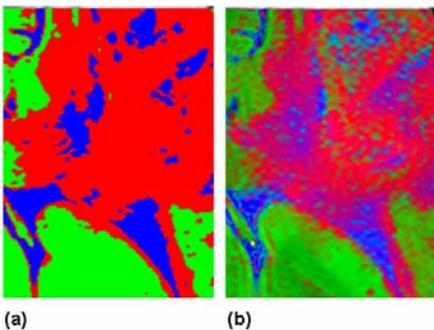


Figure 4. Comparison of (a) nosologic map obtained with neural network trained in supervised mode and (b) nosologic map obtained by inverse Laplace transform method [5]. Correspondence is of 86.1 % for this example.

Image Measurement and Analysis

CSI was performed axially to obtain spatial distributions of metabolite concentration across the lesion, TE = 30 ms and VOI of 96 cm³ (80 x 80 x 15 mm). Relaxometry studies were performed using the standard multi-echo sequence (CPMG) with 16 echoes, with a base echo time TE = 22 ms and 8 axial slices 5 mm thick centered at the tumor. The relaxation image parameters were set according to CSI voxel matrix; two slices were included within the CSI matrix. The spectroscopy data analysis was performed based on relative values. The critical Cho/NAA ratio value for which a tissue was considered malignant was 1.3 or over. The spectra were considered atypical if the Cho/NAA ratio had a value between 0.9 and 1.29. For the analysis of relaxation data, a special image processing algorithm was developed to extract the magnetization decays for different regions of interest or ROI's coming from CSI voxels. The decay patterns were classified according to a different state of the tissue (normal, pathologic, necrotic or edema) on comparison with the CSI data, using it as a sort of virtual biopsy, as shown in Figure 1. A perceptron type neural network was used. It included two hidden layers consisting of three neurons each one and an output layer consisting of two neurons, as shown in Figure 2. To provide an input with enough time resolution to separate the different decay patterns, at least twenty bits were used. All exponential decay patterns were normalized to intensity one for the first echo time and in order to convert them to a binary number, i.e., for the neural network input, a threshold was used in the following way: any time the decay pattern was above the threshold value a logic one was assumed, otherwise a logic zero. Since the relaxation decay was only sampled for eight echo times, interpolation was needed. The threshold was chosen to discriminate between decay patterns, i.e., imposing noticeable differences in the number of significant bits. Training was performed with the back-propagation algorithm in supervised mode only. To obtain the nosologic map resulting from the neural network classification a color code was used: red to indicate tumor tissue, green to indicate normal or unaffected tissue and blue to indicate edema or necrotic tissue.

Results and Discussion

In Figure 3, the results for the training of the neural network for a particular case are shown. The learning plot indicates that the error rise for a certain number of iterations and after that point further training becomes useless. All the cases analyzed in this work used 2000 iterations, with an average processing time of approximately 5 minutes. The nosologic maps obtained by the neural network method were compared with similar maps, i.e., using the same type of information, obtained with a method previously derived [5] that uses an inverse Laplace Transform algorithm (ILT) to determine the relaxation rate spectra for each voxel and its correlation with the spectroscopic data. An example of the comparison is shown in Figure 4. An analysis of the figure reveals a great level of correspondence between both maps, although the map obtained with neural network exhibits less detail and color intensities that do not vary over the regions. Another difference exist in the processing time, the neural network method takes about 5 minutes for the training while the ILT method takes about the same time for a single relaxation rate spectrum necessary for the correlation of relaxation rates with spectroscopic data. This result points in favor of using the neural network method to obtain nosologic maps in a reasonable time, particularly if a high number of images have to be analyzed as happens in 3D treatment planning for radiotherapy or radiosurgery.

Conclusions

The methodology presented in this work clearly yields nosologic maps that allow for the segmentation of brain tumor images with appropriate spatial resolution for therapeutical needs. Its use can be extended to combine images obtained from other modalities, such as diffusion weighted images. Finally, image registration for different data such as relaxometry or diffusometry seems to be the best way to assess a confident segmentation of the tumor image.

References

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