Automated brain data segmentation and pattern recognition using ANN.

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Abstract—In this project we implement an artificial neural network (ANN) algorithm to perform the segmentation of brain MRI data. The multispectral characteristics of MR images with different modalities such as T1, T2 and PD are exploited to segment different brain tissues. The ANN algorithm used in this implementation is the Learning Vector Quantization (LVQ) network. The images required for training and test are obtained from a simulated brain database integrated in the McConnell Brain Imaging Center (McBIC) of McGill University’s Montreal Neurological Institute. The results of the segmentation algorithms are qualitatively compared to the phantom images to mask each tissue. Our results suggest excellent brain tissue segmentation. We plan to exploit our results in formulating biologically plausible models for automated tumor detection.

I. INTRODUCTION

A. Why is MRI a multispectral imaging technique?

MRI is an imaging technique based in the measurement of magnetic field vectors generated after an appropriate excitation with strong magnetic fields and radio-frequency pulses in the nuclei of hydrogen atoms present in the water molecules of the patient’s tissues. Given that the content of water differs for each tissue (bone and muscle, for example), it is possible to quantify the differences of radiated magnetic energy, and have elements to identify each tissue. When specific magnetic vectorial components are measured under controlled conditions, different images can be acquired, and information related to tissue contrast may be obtained, revealing details that can be missed in other measurements. For the present study, I will consider T1, T2 and PD weighted images. (see Fig. 1)

![MRI multispectral images considered in this study](image)

B. What is Segmentation ?

The problem of segmentation is central to many image processing applications, and owes its importance to the need of identify or distinguish objects from a background or pinpoint objects embedded in other objects such as in the case of a tumor growing in the Cerebrospinal Fluid (CSF) region. There are four typical approaches segmentation. The Threshold techniques, where the classification of each pixel depends on its own information such as intensity and color information. This technique is efficient when the histograms of objects and background are clearly separated. The Edge-based methods are focused in detecting contour. They fail when the image is blurry or too complex to identify a given border. The Region-based segmentation, in which the concept of extracting features (similar texture, intensity levels, homogeneity or sharpness) from a pixel and its neighbors is exploited to derive relevant information for each pixel. A more sophisticated and recent method called Connectivity-preserving relaxation uses spline curves and modifies them (shrink/stretch) applying energy functions. Finally, the Cooperative Hierarchical Computation approach uses pyramid structures to associate the image properties to an array of father nodes, selecting iteratively the points that average or associate to a certain image value.

In the specific case of Brain MRI, the problem of segmentation is particularly critical for both diagnosis and treatment purposes. In these cases, the accurate location of a lesion is directly related to an early detection of a potential pathology, as well as to minimizing the damage to healthy tissues that can be caused by therapy procedures such as radio-surgery. The brain MRI offers a valuable method to perform pre and post surgical evaluations, which are key to define procedures and to verify their effects. Therefore, it is necessary to develop algorithms to obtain robust image segmentation such that the following may be observed:

- Automatic or semiautomatic delineation of areas to be treated prior to radio-surgery
- Delineation of tumors before and after surgical or radiosurgical intervention.
- Tissue classification: volumes of White Matter, Gray Matter, Cerebrospinal Fluid (CSF), Bone, Muscle (Skin), and Abnormal Tissues.

C. Why are ANN’s good for segmentation?

MR images are large data sets with an important number of independent variables and complex relationships, that usually show a nonlinear character that makes classical statistical
methods particularly inappropriate for their analysis. This suggests that ANN are good candidates to analyze such MR data and classify different tissues in terms of texture, intensity or contrast.

Several research in brain MR image segmentation using neural networks has been suggested in literature. The use of Self Organizing Feature Map (SOFM) ANN based algorithms\[1\] in T2 images shows excellent results in the classification of white matter, gray matter and cerebral spinal fluid (CSF). Other studies \[2\] based in modified learning vector quantization (LVQ) ANN show the potential of these architectures in the case of supervised classification and proved more convenient than traditional ANN approaches such as back-propagation ANN. Hopfield neural networks (HNN) also prove to be efficient for unsupervised pattern classification of medical images \[3\], particularly in the detection of abnormal tissue with two or three channels data segmentation. In any case, it is of primary importance to establish methods to select the features used as input for these networks, which are usually obtained from the neighborhood of a certain number of pixels, which is specially critical in pixels located in boundaries of image segments \[4\].

D. Simulated Brain DB:

Despite the relative success of MRI in the treatment of brain pathologies, it must be noted that an important part of the effort of diagnosis and location of lesions is made manually, consuming valuable human resources and making it prone to error derived from a fatigued analyst. On the other hand an image acquisition problem, may involve motion of the patient, noise, motion of fluids inside the body, motion of organs, parameter-derived measurement limitations, among others. For a same patient, different measurement conditions can render absolutely different images in terms of size, contrast, thickness and any other imaging parameter. These problems render in vivo acquired data not appropriate for the design of robust analysis systems. The use of simulated MRI is an alternative to alleviate such situation, as the use of realistic synthesized images isolate the algorithm design and test processes from the complications mentioned above. For this project, we used the Montréal Neurological Institute, McGill University, McConnell Brain Imaging Centre (McBIC) \[8\].

This database is the result of a research work developed at McBIC and contains quantitative 3-D investigation of brain structure and function. Different techniques are used for the imaging of anatomical and functional aspects of the brain. These include Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS), functional MRI (fMRI), and anatomical MRI (aMRI)

II. METHODS

The following subsections describe the ANN implementation of this project.

A. Network Architecture. Learning Vector Quantization Networks \[4\]

LVQ’s are characterized for having two complementary layers. The first one is called the competitive, and is responsible for the automatic definition of subclasses for the input vectors. Its neurons distribute themselves to recognize frequently presented input vectors. The next stage, called linear, associates the subclasses found in the previous part to target classes. The advantage of these networks over perceptrons, is that they are able of classifying any set of input vectors, regardless of the linear separability of the input set. To have an appropriate classification, the number of output nodes should be equal to the number of classes. Each class must be assigned “enough” competitive neurons. The use of LVQ , and in general, of competitive networks, has been reported in engineering literature \[3\], \[2\], \[1\] as an appropriate tool for compression and segmentation of images.

![LVQ Architecture](image)

For our MATLAB implementation we use the following description:

- **Input Layer** – 4 Features for each MRI modality (T1,T2,PD) – Total of 12 Nodes
- The features are: Mean, Standard Deviation, Minimum Value and Maximum Value
- **Hidden (Competitive) Layer** – Total of 21 Nodes
  - 3 Nodes per Output Node
- **Output (Linear) Layer** – Total of 7 Nodes
  - 7 possible Tissue Classes such as white matter, gray matter, CSF, skull, scalp, etc.

![Learning Vector Quantization Network](image)
B. Network Training and Testing

LVQ belongs to the supervised-learning ANN’s. 190 points are chosen according to their location in the phantom images to generate the correspondence between the coordinates of the pixel and its corresponding class [4]. For computational reasons (MATLAB vectorization) features of the whole image are extracted and stored. Then, specific points included in each phantom (class), were designated as the training set. Tissue samples are discriminated like this:

- 30 Samples of each Tissue Class.
- 10 Samples of Tumor Tissue.

The network is tested with the whole image. The results shown in the next section.

III. Results

We present qualitative comparison results of the segmented image and the phantom image. The performance of the network is derived from the MSE value. No further improvement in the MSE is observed after epoch 23 as shown in Fig. 4, with a performance measure of 0.04812.

Computationally, the implementation of this algorithm is very efficient. Three $256 \times 256$ images (T1, T2 and PD) are processed in less than 4 seconds to generate a segmented image. Most of the time is spent in the training, with an approximate rate of 2.12 epoch/sec. The processing times for each part of the algorithm are shown in Table I.

<table>
<thead>
<tr>
<th>Time [s] / 50 epoch</th>
<th>Time [s] / 25 epoch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preprocessing</td>
<td>1.14</td>
</tr>
<tr>
<td>Training</td>
<td>22.45</td>
</tr>
<tr>
<td>Segmentation</td>
<td>3.92</td>
</tr>
</tbody>
</table>

The comparison of the segmented images and phantom images is presented in Figs. 5 and 6 respectively.

IV. Discussion

After a qualitative comparison of phantom images and the corresponding segmented images, the classification of white matter, grey matter and the inner part of the CSF tissues shows excellent robustness. The segmentation is not so clear in the external layers of the brain, as there’s not a clear classification of tissues corresponding to scalp, skull and the external portions of CSF. However, the most significant problem regarding this implementation is the misclassification of tumor tissue. From the experiments, it can be concluded that the algorithms used for the simulation of a normal brain are different from the ones of the tumor brain, as can be seen in figures 7 and 8. This seems to be the reason for the misclassification the values of white matter for normal brain.
segmentation. The same behavior can be seen in Fig. 9.

V. CONCLUSION

LVQ based ANN’s offer promising results in the task of classifying brain tissue. Given that the correct classification of tissues depend heavily on the local texture values, it is necessary to include features that can measure this index. It is expected that fractal analysis values offer better description of the texture values around each pixel. An important effort should be devoted to the proper segmentation of in-vivo MRI, as a measure to include the many variables that affect this imaging technique, and also to derive an algorithm that performs image registration (give the same geometrical properties to images obtained with different technologies) as an intermediate step to segmentation. It is fundamental to create a data structure susceptible of vectorization as a measure to speed up the analysis process. The results obtained in this project are really good in terms of computational efficiency.

VI. FUTURE WORK

The results in this paper are very encouraging and seem to be appropriate to integration with the mainstream of my research. The tasks that can derive from this, include the integration of features derived from Fractal Analysis which describe Local Texture or Ruggedness in terms of an estimated value called Hurst Coefficient. These results are expected to be used in conjunction with Wavelet Multiresolution Analysis to exploit the typical localization in Time/Space and Frequency/Scale domains characteristic of this mathematical model. Future stages of this work also require consider the problem of Medical Image Registration, to take advantage of existing medical images obtained through different technologies such as PET or Computerized Tomography. Another key part of the continuation of this project, is the use of in-vivo MRIs to adjust the current results obtained here with simulated MRI, with the requirements of real brain MRI. The inclusion of other competitive Network architectures such as
Self-Organizing Maps is also considered, as reports show their utility in segmenting brain images.

VII. ACKNOWLEDGMENT

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REFERENCES

[5] Mathworks Inc. MATLAB Neural Networks Toolbox Documentation; v.4.0.1