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A Hybrid Fuzzy Neural Networks for the Detection of Tumors in Medical Images

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Abstract: In this study, we propose an approach to detect suspect zones or tumors in medical images. The idea is to define with precision the existence of different kinds of lesions using a hybrid system, which combines Fuzzy Neural Networks and Expert System. After applying a method of image segmentation to extract regions (by region growing algorithm or by mathematical morphology algorithm), the fuzzy neural networks detect the suspect regions, which are validated by an expert system to determine the nature of lesions. Some of experimental results on brain images show the feasibility of the proposed approach.

Key words: Fuzzy Neural Network, Expert System, Medical Images, Tumors, Diagnostic, Interpretation

INTRODUCTION

Artificial vision aims to replace the human vision in various fields such as aerial, robotics, nuclear plants as well as in medical imagery. Image interpretation represents an essential phase in the chain of the vision process by computer. Several methods have been proposed based on neural networks, genetic algorithm and expert systems [1, 2]. Hybrid systems combining the fuzzy logic and artificial neural networks (Fuzzy-Neural Networks) have been proposed. There are different approaches for this combination. Nauck and Kruse [3] have proposed competitive Fuzzy-Neural networks models that are of Fuzzy-Neural Networks form less used ; the two techniques are used in a competitive manner for the same mark. The Neural network is used as meadow/post processing for the fuzzy system, but the neural system does not change anything (parameters) to the fuzzy system.

The second proposed model is *The* Cooperative Fuzzy-Neural networks model [3] a learning process is used, to learn some parameters (intervals, fuzzy rules, or weights of rules) of the fuzzy system. Neural networks and fuzzy systems are no longer separated. Recent approaches of Fuzzy-neural networks are formed of this type. Nauck and Kruse have proposed two hybrid fuzzy-neural approach using fuzzy intervals: NEFCLASS [3] and NEFCON [3-5].

They are derived from a fuzzy perceptron model that defines basic properties of this type of Fuzzy-Neural networks model. The fuzzy perceptron has the same architecture of a generic neuron system, but weights, and this case values of membership, are modelled in fuzzy area, and outputs, and functions of propagation are changed in agreement with weights.

NEFCON is used in application of control with learning by strengthening, while NEFCLASS is used for the analysis and the classification of data by supervised learning.

The Proposed Method

Image Segmentation: A major problem in image analysis is to describe more compactly the visual information that they contain. This problem can be solved either by finding local discontinuities of the grey level function: edge, detection, either by searching areas of the image which present some homogenous properties: region segmentation.

So to segment our images, two techniques have been used: the segmentation by region growing and the segmentation by mathematical morphology.

The segmentation by region growing [7-9] consists in using the proceeding SPILT proposed by Pavlidis and the hierarchical sequence of merging criterion. The idea is to minimise the cost function by merging neighboring regions which verify a predicate and whose union gives the best local quality. The properties that the regions which verify a predicate and a local quality function. The mathematical morphology is based on transformations of the collection to analyse that is compared to a collection called element structuring. The target is to extract morphological and structural characteristics.

Characteristics of images segmented by growing region are presented as follows:

* Number of regions of the image
* Surface of each region
* Maximal gray level
* Minimal gray level
* Coordinate of the rectangle
* Summons intensity
* Summons squares
* Number from point frontier
* Number of neighbours of each edge point
* Coordinate and level gray of each neighbour

Attributes Chosen: The surface of the region, the compactness that represents the factor of circularity, the mean gray level of the region, the variance and the elongation that, in our case, has been calculated by using axes of parallel inertia so as to marry the best way the form of the region concerned.
These attributes extracted from regions of the image are presented to entries of the fuzzy-neural networks for the detection.

Detection of Anomalies by Fuzzy Neural Networks: After the stage segmentation [6, 9], the regions and photometric and geometric features such as compacity, gray value average, gray value variance, surface and elongation are extracted. These extracted features are presented to entries of the fuzzy-neural networks for the detection.
To each of these features are associated three predicates (Table 1) making call to fixed thresholds after having examined characteristics of regions of several medical images representing the cranium.
For this stage, we have used a Fuzzy-Neural Network that is a prototype of the NEFCLASS model quoted if over, and having an Input layer counting the morphological attributes, a first hidden layer where are calculated degrees of membership, a second hidden layer for the blurred rule evaluation and an output layer counting the result (Fig. 1).
The input layer contains five neurons representing the chosen characteristics for each region of the image. For each entry neuron, we allocate three membership areas (fuzzy set), that represent predicate intervals quoted previously. For example:

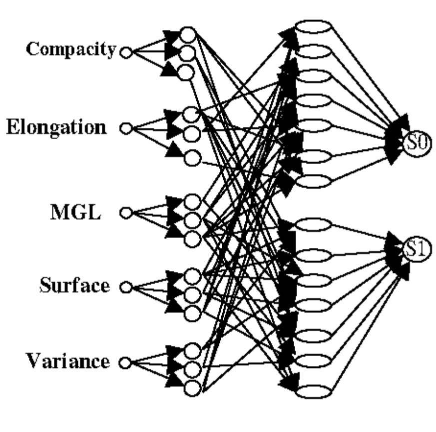

Fig. 1: Fuzzy-neural Networks Architecture

The first hidden layer contains fifteen neurons representing membership degrees of each neuron of entry to the three fuzzy collection admitted (the three predicates), such that each neuron of the input layer is connected with three neurons of the first hidden layer.

$$\mu_{ij}(x) = \begin{cases} x\text{-}a / b\text{-}a & ; \text{If } a < x < b \\ x\text{-}b / c\text{-}b & ; \text{If } b < x < c \\ d\text{-}x / d\text{-}c & ; \text{If } c < x < d \\ 0 & ; \text{Otherwise.} \end{cases}$$

For $i= 1,2,3$
For $j=1,\ldots,5$

The second hidden Layer (Layer of Rules) is represented by collection of rules evaluated by a function of aggregation (in our case the function is MIN -MAX), these last are an estimation of truth rate of each rules. These rules are used to detect the presence of one or several anomalies in each region of the image.
The calculation of rules will be undertaken as continuation:
For the rule: If X1 is $\mu 1$ and X2 is $\mu 2$ and X3 is $\mu 3$ Then C1
We will have R = MIN ($\mu 1$, $\mu 2$, $\mu 3$), where X1, X2, X3 represent entries of the system.
We have used fourteen rules for the detection as presented in Table 2. The output layer contains two neurons, these last cost initially 0, and take values 1 or 0 according to whether the region presents an anomaly or not. These values are calculated as continuation:

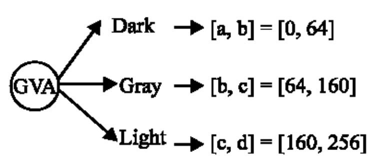

Fig. 2: Neurons Associated to Gray Value Average

For all rules connected to the output1 and to the output2, the neuron of exit takes:
Output = MAX(R_0, …, R_n);
for n : the number of rule connected to the same output.
If the region is suspicious then:
Output = (1,0);
If the region is not suspicious then:
Output = (0,1);
Any other labeling returns to unclassified region.

Learning Phases: We have used a supervised learning by gradient retro propagation. This one is employed to adjust fuzzy intervals which will be used in phase of detection.

The algorithm of the learning is:
For each region of the image to make the processing following:

* To propagate its characteristics through the system and to determine outputs.

* For each output, to determine Delta values, such that:

$\delta_{output\,i} = \text{Output\_Desired}_i - \text{Output\_calculated}_i$

* For each neuron of the layer of rules a_R such that $a_R > 0$:

a. Determined Delta values:

$\delta_{rule} = a_R(1 - a_R) \sum W(R, \text{Output}_i)\, \delta_{Output\,i}$.

b. To find μ_k that causes the minimum in the totality of μ connected to the even rules:

$W(\mu_k, R)(\mu_k) = \text{MIN}\{ W(\mu_{ij}, R), (\mu_{ij}) \}$

such that $\mu_{ij} \in$ first hidden layer.

* To determine the input X connected with this minimum.

c. To adjust areas of this input by determining Delta values for each parameter of areas(a, b, c, d) such that:

$\delta_b = \delta_{rule}$ (d-a) Sign (X-b)

$\delta_a = -\delta_{rule}$ (d-a) + δ_b

$\delta_c = \delta_{rule}$ (d-a) Sign (X-c)

$\delta_d = \delta_{rule}$ (d-a) + δ_c

Specification of the Nature of Anomalies: Expert systems know equally to manipulate vague data and uncertain knowledge. During this phase, we have used next criteria: Limit (regularity or irregularity (well limited, pain limited or blurred), density (homogeneity of region) and size (more the tumor is great, more the crafty potential is raised).

Knowledge Base: Represents the different features of region to define (compacity, MGL, surface, elongation and variance).

Rule Base: Rules defined in this basis are: Rules of malignancy prescription: If an anomaly is considered as a crafty tumor, it presents the following signs: single, great, irregular, pain limited, heterogeneous, hypodense.

Rules of Benignity Prescription: The tumor is benign if it presents the following signs: It can be multiple, generally small and well limited, regular.

Table 1: The Extracted Attributes and Their Predicates

Attributes	Predicates		
Surface	Small	Midium	Large
Mean gray level	Dark	Gray	Bright
Variance	Not Homogeneous	Homogeneous	Very homogeneous
Elongation	Not Elongated	Elongated	Very Elongated
Compacity	Not Compact	Compact	Very compact

Table 2: Rules Used for the Detection of Anomalies

With: Rule 0 $\longrightarrow$ Anomaly detected

Rule 10 $\longrightarrow$ No anomaly

No. Rule	Compacity	Elongation	GVA	Surface	Variance
0	\	Elongated	\	Large	Not homogeneous
1	\	\	Dark	Large	Homogeneous
2	\	Not elongated	Bright	Medium	\
3	\	\	Bright	Small	Not homogeneous
4	\	Elongated	Bright	Large	Not homogeneous
5	Not compact	Not elongated	Bright	\	\
6	Bit compact	Very elongated	Bright	\	\
7	\	\	Bright	Small	Very homogeneous
8	Compact	Not elongated	\	Small	\
9	\	\	Gray	Small	Very homogeneous
10	Compact	Not elongated	Dark	Medium	Not homogeneous
11	Not compact	Not elongated	Gray	Medium	\
12	\	\	Bright	Large	Homogeneous
13	Very compact	\	Gray	Small	\

Engine of Inference: Nucleus of the expert system that combines and exploits the basis of rules and the basis of data. The conceived expert system during this phase is an expert system that determines the nature of anomalies detected by the fuzzy-neural networks, where one takes in consideration that tumors, any other anomaly is labelled not recognized.
We will calculate t the rate of recognition such as follows: TR that is equal to:

TR = (Nbr crafty tumors + Nbr benign tumors) / Nbr anomalies.

TESTING AND RESULTS

This method has been tested on medical images representing MRI of human images representing the cranium. Showing anomalies (tumors) (Fig. 3 and 8). These images were segmented by the growing region or mathematical morphology (Fig. 5 and 10).
The extracted region features are fed to the Fuzzy neural network to detect suspect regions. The network interpreting the image is shown on Fig. 6 and 7.

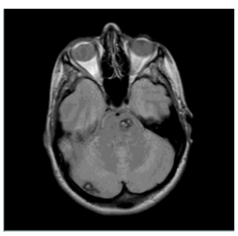

Fig. 3: Original Image

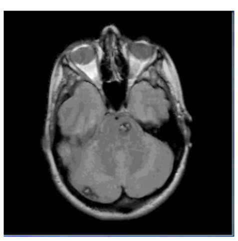

Fig. 4: Filtered Image

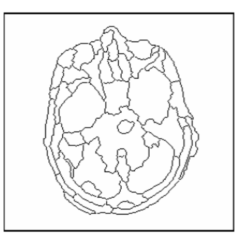

Fig. 5: Segmented Image by Growing Regions

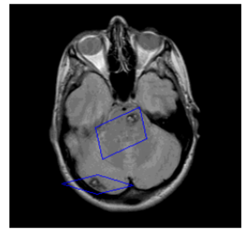

Fig. 6: Original Image with Anomalies Detected

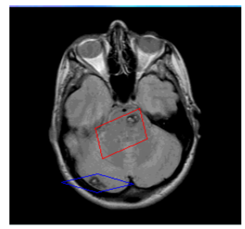

Fig. 7: Original Image with Anomaly Specified, With: Performance=99.31%. With: Rate of Recognition=50%

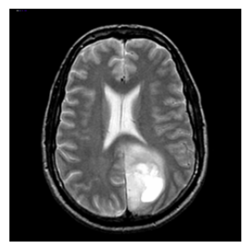

Fig. 8: Original Image

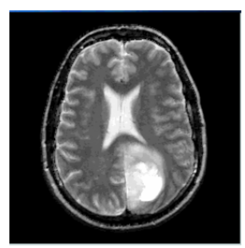

Fig. 9: Filtered Original Image

Fig. 10: Segmented Image by Mathematical Morphology, Superposed on the Original Image

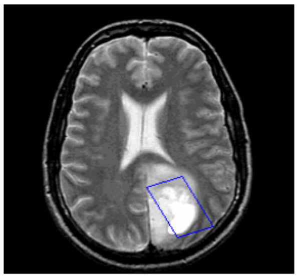

Fig. 11: Image with Anomalies Detected With: Performance=99.44%

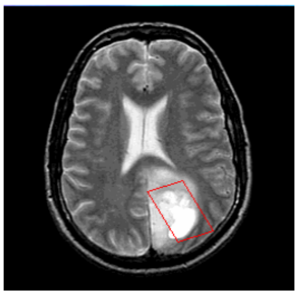

Fig. 12: Image with Anomaly Specified, with Rate of Recognition =100%

The suspect regions which detected by fuzzy neuronal network are validated by an expert system to determine the nature of lesions. The results are shown in Fig. 7-12. We note that more than ten images were used for test and training, but three images of test give results.

CONCLUSION

We have proposed in this paper an approach of medical image interpretation based on regions primitives by fuzzy-neural networks and expert system. We have made tests on brain images, the obtained results are satisfying and our system is able to make reliable predictions with a discriminating performance comparable to that of experienced pathologists. This method can be generalized to other medical images in order to detect and identify various kinds of anomalies. It can also be used to analyze other types of images such as: satellite images and aerial.

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REFERENCES

1. Parigot D. Un mini système expert (application: diagnostic sérologique d'une hépatite virale) http://www.edu.polytechnique.fr
2. Tuan Anh T. Un mini système expert appliqué au diagnostic», http://www.dockitsoft.com
3. Nauckl, D. and R. Kruse. Neuro-Fuzzy Classification with NEFCLASS. Institute of Information and Systems of Communication. Faculty of Data-Processing, University of Magdeburg (Germany), http://fuzzy.cs.uni-magdeburg.de/˜nauck
4. Nauck, D., 1994. Building neural fuzzy controllers with NEFCON-I. Fuzzy Systems in Computer Science, Artificial Intelligence, pp: 141-151.
5. Nauck, D. and R. Kruse, 1993. A Fuzzy Neural Network learning fuzzy control rules and membership functions by fuzzy error back propagation. Proc. IEEE Int. Conf. Neural Networks.
6. Benamrane, N., 1994. Contribution à la Stéréovision par Mise en Correspondance de Régions. Ph.D. Thesis, University of Valenciennes, France.
7. Pavlidis, T., 1977. Structural Pattern Recognition. Spinger-Verlag, Berlin Heidelberg, New-York.
8. Monga, O., 1987. An optimal region growing algorithm for image. Intl. J. Pattern Recognition and Artificial Intelligence, pp: 351-376.
9. Benamrane, N., 1993. Image matching: A new structural method based on regions. Progress in Image Analysis and Processing III, 7th Intl. Conf. Image Analysis and Processing. Edited by Sebastiano Impedovo, Singapore, New Jersey.