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A COMBINED NEURO–FUZZY APPROACH FOR CLASSIFYING IMAGE PIXELS IN MEDICAL APPLICATIONS

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This paper is concerned with classifying image pixels into three sets of pixels: contour, regular, and texture. When properly processed, classified images can represent foundations for diagnostic purposes. A neuro-fuzzy approach was used to take advantage of neural network's ability to learn, and membership degrees and functions of fuzzy logic, respectively. The method is based on the spatial properties of the image features and makes use of multi-scaled representations of the image. A training set was used to create and train the classifier system. The classes were represented as fuzzy sets with degrees of memberships. Each pixel was assigned a degree of membership for each of the three fuzzy subsets. Classified pixels were finally shown as three separate images each representing a set. The method showed high quality classification for images of simple components. This approach would be highly attractive in the biomedical field due to the vast availability of images.

K e y w o r d s: image processing, biomedical images, pixel classification, pixel classes, neuro-fuzzy approach

1 INTRODUCTION

Problems encountered in the field of image processing frequently reside in the vagueness of the data under study. Over the last few decades neural networks and fuzzy systems have established reputation as an alternative approach to information processing. Both have certain advantages over classical methods, especially when vague data or prior knowledge is involved. However, their applicability suffers from several weaknesses of the individual methods.

A neuro-fuzzy approach as a combination of neural networks and fuzzy logic has been introduced to overcome the individual weaknesses and to offer more appealing features. The ultimate goal of applying such a system is to get rid of imprecise information present in an image such as pixel grayness ambiguity, geometrical segmentation of the image and the uncertain interpretation of a scene [2]. This exploits, respectively, the learning capabilities and the descriptive power of systems, thus providing results characterized by a high interpretability and good degree of accuracy [1, 2].

An image feature is what distinguishes and characterizes it from other images [3, 4, 5]. The aim of the neuro-fuzzy approach application is to extract these features pixel by pixel and classify them into three sets of classes: Regular, Texture and Contour. The concept of the edge is greatly connected with feature extraction methods [7, 8].

The difficulty of such a system lies in detecting textures the presence of which dictates the use of multi-scale representation. The method proceeds without any prior knowledge or presence of any expert intervention and can be employed as a pre-processing or a post-processing stage of an image segmentation problem. It may be also used to improve the performance of some database retrieving processes [6]. Furthermore, it can be applied in biomedical context especially in human body images for purposes of analytical studies. It would ultimately lead to a system that would help after applying appropriate enhancement techniques to recognize abnormalities in the biomedical images and thus help the physician in his/her diagnostic procedures.

This paper aims at implementing the above-mentioned approach in image pixel classification. The objective is to use such an approach in developing a functioning program that will accept any input image and classify its pixels one by one into the three distinct classes indicated above.

2 METHODOLOGY

The methodology of this work entails the use of a neuro-fuzzy system, which is a software program utilizing the benefits offered by the Matlab toolboxes. The only requirement of this system is the availability of a training set that allows for a fuzzy rule base that is capable of classifying the pixels after the neural network training. This training set is constructed using training images shown in Fig. 1. These images are distinct combinations of the three classes of regions described above. The output data of the training set, depicted in Fig. 3, are images created to model the ideal output (three classes) of the classifying algorithm. The training data are used to generate fuzzy inference systems (FIS) for each of the three classes. The training set for each class FIS consists of four columns three of which are for each scale representation (acting as

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Fig. 1. Training images that are distinct combinations of the three classes of regions.

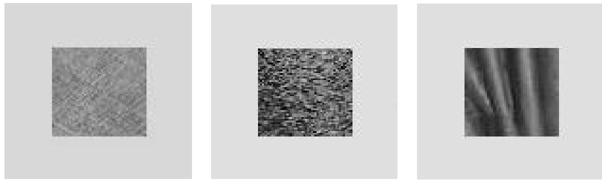

Fig. 2. Tuning images used in the classification process.

Fig. 3. The ideal output of the training images.

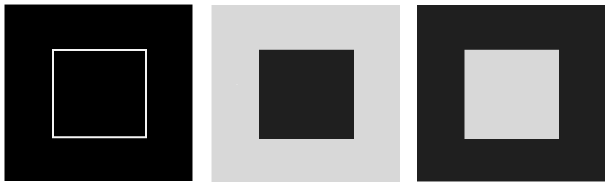

Fig. 4. The ideal output of the tuning images: (a) contours (b) regular (c) textures.

the three inputs of the system) of an image and the fourth is the output column representing the ideal response. The result of the training are three fuzzy systems, each FIS contains a number of fuzzy rules that were used in the classification process. Once the rules are generated, they are tuned by adaptive Neuro-fuzzy inference systems using another group of images shown in Fig. 2. These images were created in the same way as that of training data. In order to achieve parameters that most accurately classify a pixel into a class the group of images were chosen with distinct regions. The three different regions can be easily highlighted and used as ideal outputs for the classification of the images as shown in Fig. 4.

The classification approach of a grey image begins by taking multiple scale representation for the image using a 3 by 3 averaging filter consecutively applied to each input image. Here, the first source (original image) was used as the finest scale, the second was the middle scale, and the third was the coarsest scale.

Assuming 3 different scale representations of an $M \times N$ image, the edge strength value for each pixel in each scale representation was evaluated using the Sobel gradient method [10]. Based on this value, a set of fuzzy rules for each image is extracted in order to classify that pixel into one of the above-mentioned classes. The k^{th} rule is given by [9]:

$$\text{IF } E_{i,j}^{(1)} \in A_k^{(1)},\ E_{i,j}^{(2)} \in A_k^{(2)} \text{ and } E_{i,j}^{(3)} \in A_k^{(3)}$$
$$\text{THEN } g_{i,j} \in C_p \text{ with the degree } V_{kp}$$

where:

$E_{i,j}$ is the pixel edge strength for the r^{th} representation, $i = 1, 2, \dots, M$, $j = 1, 2, \dots, N$, $r = 1, 2, 3$

$g_{i,j}$ is the pixel of the given representation

A_k^r are fuzzy sets defined over the variables $E_{i,j}^{(r)}$ using the Gaussian membership functions, $k = 1, \dots, K$

C_p are the three output classes, $p = 1, 2, 3$

V_{kp} are fuzzy singletons representing the degree to which a pixel belongs to a class.

The Gaussian membership value for each input is evaluated according to:

$$\mu_{r,k}\big(E_{i,j}^{(r)}\big) = e^{-\left(E_{i,j}^{(r)} - w_{rk}\right)^2 / \sigma_{rk}^2}$$

where:

w_{rk} is the center of the Gaussian function,

σ_{rk} is the width of the Gaussian function.

The output value of the fuzzy system for any input is calculated by:

$$y_p = \frac{\sum_{k=1}^{K} \mu_k\big(E_{i,j}\big) v_{kp}}{\sum_{k=1}^{K} \mu_k\big(E_{i,j}\big)}, \quad p = 1, 2, 3$$

where:

$\mu_k\big(E_{i,j}^{(r)}\big) = \prod_{i=1}^{n} \mu_{ik}\big(E_{i,j}^{(r)}\big)$ is the activation strength of the k^{th} rule.

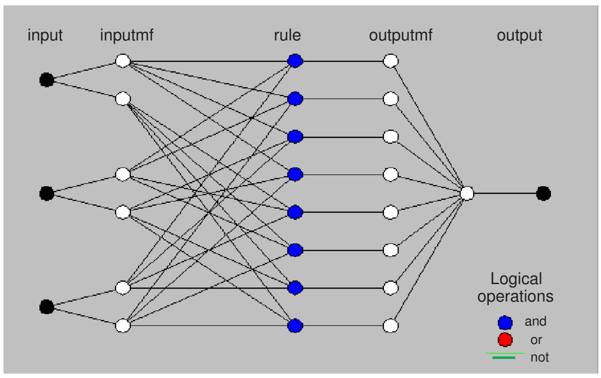

Fig. 5. The structure of the obtained neural network.

The structure representing the neural network obtained from the learning of the fuzzy systems is shown in Fig. 5. The three inputs represent each pixel value of the three scale representations. Each of the training sets produced a Fuzzy Inference System that contained eight

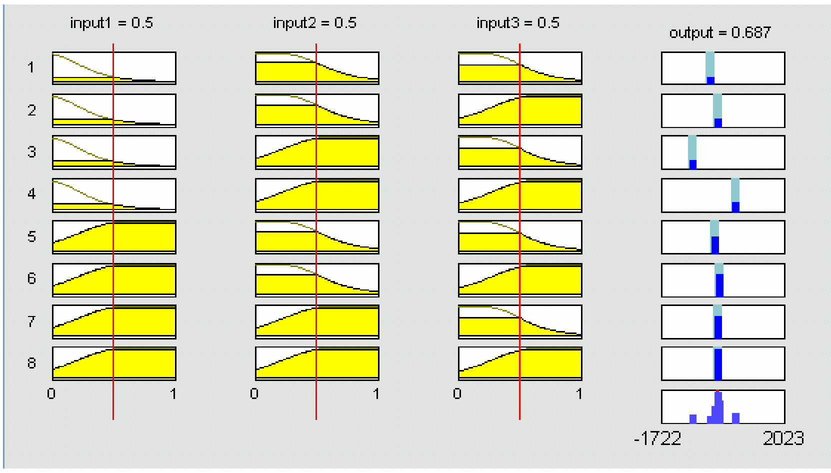

Fig. 6. The fuzzy rule base employed to derive the regular class.

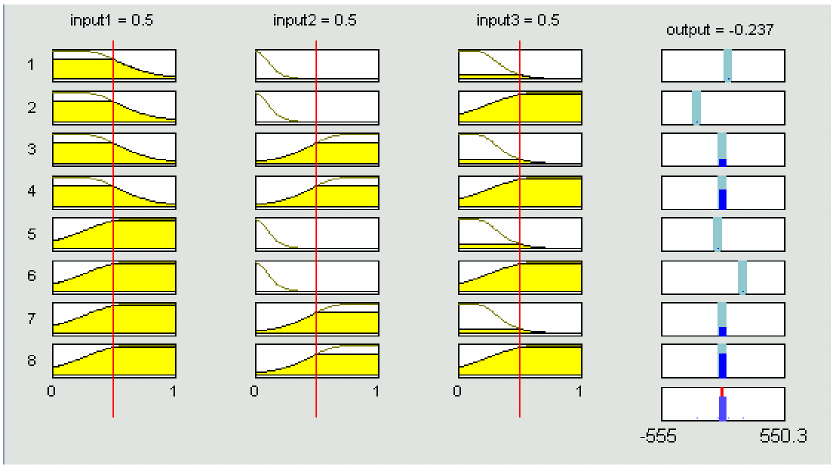

Fig. 7. The fuzzy rule base employed to derive the contour.

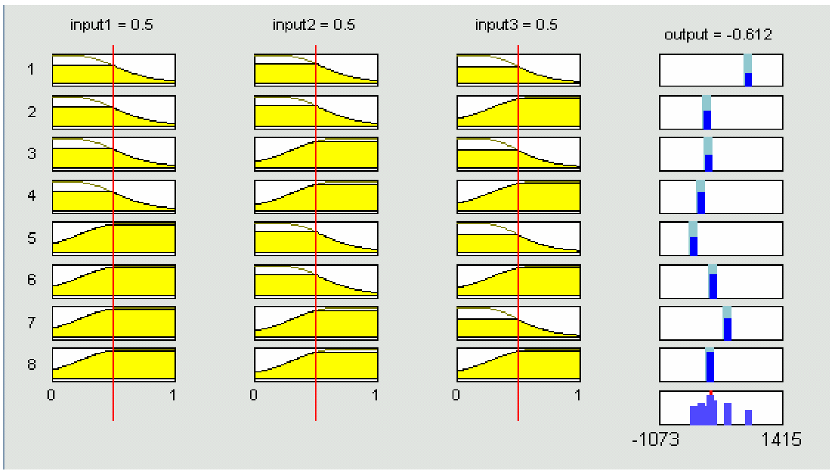

Fig. 8. The fuzzy rule base employed to derive the texture class.

fuzzy rules. Each input was given two Gaussian membership functions, and the output was represented by two linear membership functions. The outputs of the eight rules are condensed into one single output, representing that system output for that pixel. The rules are listed in Figs. 6 to 8.

After obtaining all three outputs of the three systems for each pixel, program algorithm is applied to calculate and compare the membership belonging to a certain class. The highest membership degree is given the value one (complete truth) whereas the other two are given the value zero (complete false). This in effect assigns one class for each pixel, white being true and black being false. The

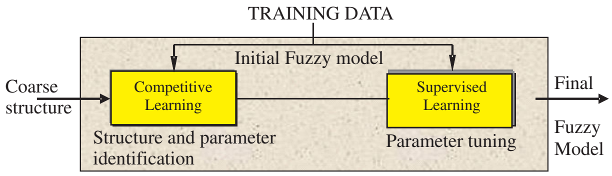

Fig. 9. Schematic block diagram of the learning scheme.

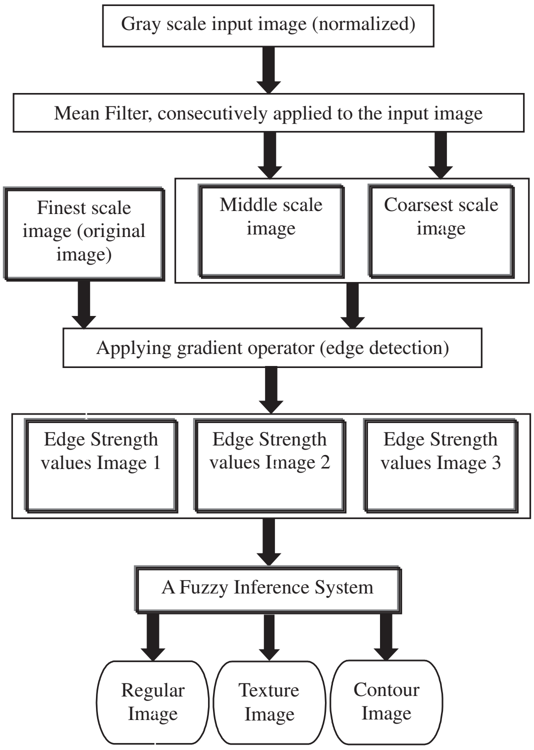

Fig. 10. The basic concept of the classification process.

image is reconstructed using these zero/one values. The result is in fact an image classified into the three different classes.

Learning in this system is defined by a two-step learning approach, *ie* , competitive to obtain parameters of fuzzy rules and supervised learning for further optimization of these parameters. The schematic diagram of the learning process is shown in Fig. 9.

A complete schematic representation of the basic concept of the classifying system is shown in Fig. 10.

3 RESULTS

The Neuro-Fuzzy approach presented here allows any ordinary person without experience in this field and with the availability of only a training set with ideal outputs to build up a system that models his/her information with no more than two or three functions based on well-known and well-established algorithms. The percentage error ranges obtained were: 2.03 for regular, 8.9 for texture, and 1.58 for contour. Figures 11 and 12 show examples of images that were classified using this system.

Applying the proposed algorithm to complex patterns would ensure its usefulness and its possible adoption as a core tool especially for segmentation and later on for diagnosis as in biomedical imaging. To examine the performance of the proposed algorithm, a set of images obtained from MRI and CT-scan modalities are used to classify their pixels. The tested images showed excellent results that support the arguments posed regarding the usefulness of the proposed approach. Figure 12 illustrates the application of the algorithm on an MRI image of the brain and its results. The obtained accuracy as shown in the figure is remarkably high.

The accuracy of this classifier system varied depending on the input image itself. The system showed high quality classification for images of simple components, where regions are separate and descriptive, and where the boundaries of the object came in high contrast, which corresponds to high edge strengths. Low contrast edges' problem might be solved by applying a preprocessing technique of image enhancement that would in fact increase the contrast of neighbouring pixels, thus, increasing the edge strength to make it easier for the system to detect the contour lines.

4 DISCUSSION

The proposed pixel classification approach presented in this paper can be further investigated to be quite helpful in the biomedical application. Since most diagnostic techniques depend on imaging modality, the majority of images and accompanying diagnosis of diseases can be fed to such a system in order to develop a technique. The technique would then use the classification to localize regions that may be used to detect any abnormalities and list the diagnosis accordingly. The application can be easily used as a pre-processing technique, where classified images can be used in a number of applications of analytical nature. Computer analysis can complement to laboratory tests for example, that might give a clearer picture of the human physiology and pathological diseases.

Biomedical imaging modalities, such as MRI and CT-scans showed high accuracy in all three classes of pixels. These results were very encouraging since these images are of great importance in the diagnosis of hard-to-detect diseases. These kinds of images have great contrast values for edges and clearer regions that allowed this approach to easily react to such images. The proposed system was insensitive to the noise imposed in these images, thus, maintaining its levels of high accuracy.

The system ability in solving the texture classification that might be extremely hard or even impossible in other methods is the main contribution of this work. Its regular class is also highly accurate, and very close to a human observer's classification. The proposed technique is a highly useful and powerful classification tool that fulfilled the independency requirement of being a self automated classification tool.

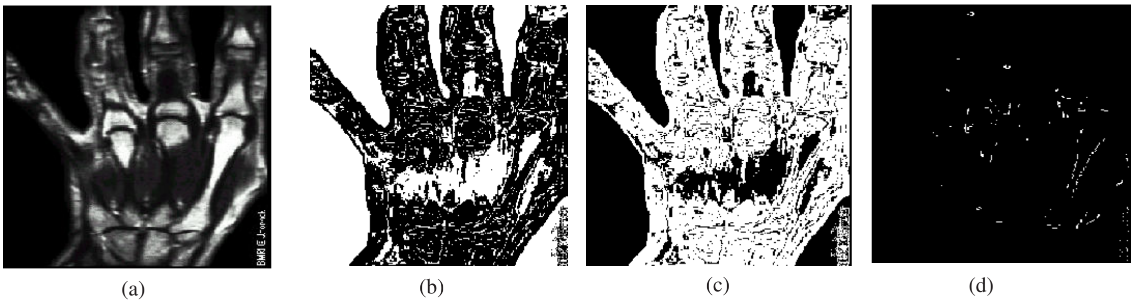

Fig. 11. Result of a hand image Classification: a) Original image b) Texture c) Regular d) Contour

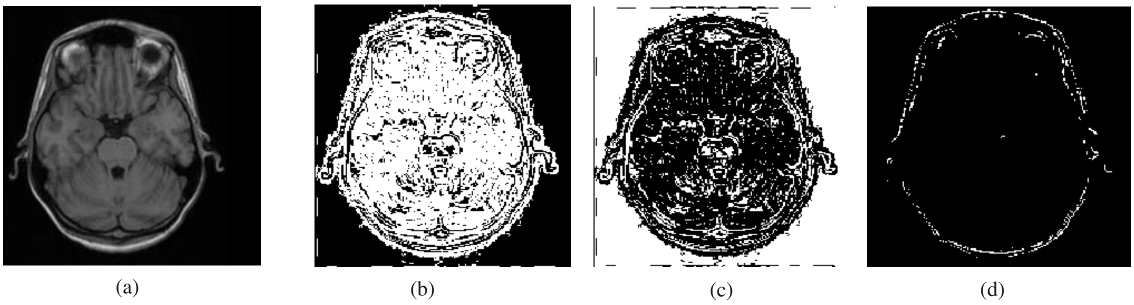

Fig. 12. Classification results for the Brain MR image a) Original image b) Texture c) Regular d) Contour

5 CONCLUSION

In this paper it was proved that neuro-fuzzy approach could be one of the important modalities in image processing, especially in the biomedical scene where most diagnostic techniques rely on imaging. The presented pixel classification tool is a highly useful, powerful, and independent of any expert or any prior knowledge. The effectiveness of this method and its ability to automatically extract the shape and texture properties from an image drive us to consider it a highly intelligent development in image processing that supports intelligent decision at low costs. The suggested approach may be enhanced by some pre-processing procedures that might boost the characteristics of the system in its classification. Some adjustments in the learning schemes or the training sets can also increase the efficiency of the system, especially choosing the optimal subtractive clustering parameters. This encourages us to subject it to future improvement and enhancement that will enrich its contribution and find ways for its real imaging applications.

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