-59-

FUZZY NEURAL NETWORK BASED CHARACTERIZATION OF DIFFUSED LIVER DISEASES USING IMAGE TEXTURE ANALYSIS TECHNIQUES ON ULTRASONIC IMAGES

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Abstract – In this study the classification of B-scan ultrasonic liver images using a novel fuzzy neural network classifier is investigated. Image texture analysis techniques were used to extract classification features. The techniques used are the Fractal Dimension Texture Analysis (FDTA), the Spatial Gray Level Dependence Matrices (SGLDM), the Gray Level Difference Statistics (GLDS), the Gray Level Run Length Statistics (RUNL), and First Order gray level Parameters (FOP). All four techniques were applied on three sets of ultrasonic liver images: normal, fatty, cirrhosis. A total of 150 cases were investigated (50 each class). with all abnormal cases being histollogically proven . In each image , a 32x32 rectangular region of -interest was selected by an expert physician. Extracted features are fed to a neural network classifier based on geometrical fuzzy sets. Starting from the construction of the Voronoi diagram of the training patterns, an aggregation of Voronoi regions is performed leading to the identification of larger regions belonging exclusively to one of the pattern classes. The resulting scheme is a constructive algorithm that defines fuzzy clusters of patterns. Based on observations concerning the grade of membership of the training patterns to the created regions, decision probabilities are computed through which the final classification is performed. Classification accuracy achieved with the proposed neural network classifier was found to be higher than that reported for physicians performing visual interpretation of ultrasound images and superior to that obtained using Nearest Neighbor classifiers.

Keywords: Ultrasound, liver, tissue characterization, texture analysis, fuzzy neural networks

I. INTRODUCTION

Ultrasound (u/s) B-scan imaging has become one of the most widely used methods of imaging human abdominal organs such as liver, spleen, kidneys, etc. This is because of its ability to visualize organs without deleterious effects.

Liver diseases are taken seriously because liver is one of the most vital organs of the human body. Liver diseases can be devided into two main categories : a) Focal diseases (e.g. hepatoma, hemangioma) where the abnormality is concentrated in a small area of the liver tissue while the rest remains normal. b) Diffused diseases (e.g. cirrhosis, fat) where the abnormality is distributed all over the liver volume.

Visual interpretation of u/s liver images by specialized physicians contributes to the decision whether a tissue is normal or abnormal. Liver tissue characterization using u/s images, mainly depends on the ability of the sonographer to observe certain textural characteristics. It was shown that the characterization accuracy using only visual interpretation for diffused diseases is around 72% [1], [2]. The presence of certain textural characteristics called "Speckle Pattern" in B-scan images, makes the use of image texture analysis techniques suitable for computer assisted tissue characterization.

A considerable number of image texture analysis techniques was developed over the years. The most common are the Laws Texture Energy Measures (TEM) [3], the Fourier Power Spectrum (FPS) [3], the Gray Level Difference Statistics (GLDS) [3,4], the Gray Level Runlength Statistics (RUNL) [5], the Spatial Gray Level Dependence Matrices (SGLDM) [6,3,4], parameters based on First Order Gray Level Statistics (FOP) [7] of an image and several techniques based on the estimation of the Fractal Dimension from an image such as the Fractal Dimension Texture Analysis Technique (FDTA) [3]. Texture analysis techniques for liver tissue characterization have been used in the past with very promising results [3,7,8]. In this study a scheme for the classification of three sets of u/s liver images (normal, fatty, cirrhosis, hepatoma) is investigated.

II. METHODS

The analysis presented in this study was performed into two main steps: (a) the extraction of tissue characterization features, and (b) the classification of the images using a fuzzy neural network classifier.

Three sets of u/s liver images were used in this study: normal, fatty, cirrhosis. All abnormal cases were histologically proven. All ultrasound images were captured using an Acuson 128 XP/10 ultrasound scanner with 3.5 MHz transducer (V328 phased array). Digital images were captured using a Screen Machine frame grabber on a PC-AT personal computer. Images were digitized with 320x256 pixels and 256 gray level distribution. Texture analysis algorithms were applied in each image on a 32x32 pixel region of interest (ROI) selected in a systematic way so as to avoid deviation in image statistics: i) All images were taken by the *same physician*, using the *same equipment*, (Ultrasound system Acuson 128 XP/10, Transducer V328 Phased Array). ii)Ultrasound *system settings*, which affect image texture, were kept the same. iii) Fatty and cirrhosis images were *histollogically proven*. iv) ROI were selected by expert physicians so as to contain only liver parenchyma (normal or abnormal) with no major blood vessels. ROI were selected along the focusing area and along the center-line of each image.

In the following section, the techniques used for feature extraction and classification are presented.

A. Image Texture Analysis Techniques

Five different image texture analysis techniques were used FOP, GLDS, RUNL, SGLDM, and FDTA. In particular, the techniques were:

i. First order gray level Parameters (FOP)

In this category the parameters are derived from the gray level histogram and they describe the gray level distribution without considering spatial independence. As a result, they can only describe echogenity of texture and the diffuse variation characteristics within the ROI. In our study we used Kurtosis (KUR) and Variance(VAR).

$$\mathrm{KUR} = \frac{1}{N}\left[\frac{\sum_i\sum_j (g(i,j)-\mu)^4}{\sigma^4}\right], \qquad \mathrm{VAR} = \frac{1}{N}\sum_i\sum_j (g(i,j)-\mathrm{MEA})^2$$

where g(i,j) is the gray level of the pixel (i,j), N is the total number of pixels in the specified ROI, *ì* & *ó* are the mean value and standard deviation of total number of pixels .

ii. Gray Level Run Length Statistics (RUNL)

This technique is based on gray level run length of the image. If we examine the points that lie along some given direction (run lengths), we will occasionally find runs of consecutive points that all have the same gray level. In a coarse texture relatively long runs occur more often, where as, fine texture contains primarily short runs. In a directional texture, the run lengths that occur along a given line should depend on the direction of the line. The feature used is Run Percentage (RP).

$$\mathrm{RP} = \frac{\sum_i^{N_g}\sum_j^{N_r} Q_{R\text{-}L}(i,j)}{P}$$

where $Q_{R\text{-}L}$ is the number of run-lengths j for gray level i , in some direction è, N_g is the number of gray levels of the image, N_r is the number of different run lengths, and P is the total number of image pixels. Run lengths for è=0^0, 45^0, 90^0, 135^0 and the sample mean and standard deviation were estimated.

iii. Gray Level Difference Statistics (GLDS)

The GLDS algorithm is based on the assumption that useful texture information can be extracted using first order statistics of an image. The algorithm is based on the estimation of the probability density of image pixel pairs at a given distance *ä=(Ä+,Äõ)*, having a certain absolute gray level difference value. Coarse texture images, result at low gray level difference values whereas, fine texture images result on interpixel gray level differences with great variances. The features used are Entropy (ENT), Angular Second Moment (ASM), Mean (MEA).

$$\mathrm{ENT} \equiv -\sum p_\delta(i)\log(p_\delta(i)), \quad \mathrm{ASM} \equiv \sum p_\delta(i)^2, \quad \mathrm{MEA} \equiv (1/m)\sum i p_\delta(i)$$

where i is two pixels gray level difference, m is the number of gray levels and $p_ä$ are the individual probabilities. Features where estimated for the following distances *ä=(d,0), (d,d), (-d,d), (0,d).*

iv. Spatial Gray Level Dependence Matrices (SGLDM)

The SGLDM algorithm is based on the assumption that texture properties of an image are contained in the overall or "average" spatial relationship between the gray levels. SGLDM is based on the estimation of the second order conditional probability density *p(i,j;d,è)*. Each value *p(i,j;d,è)* represents the probability that two different resolution cells which are on the direction specified by an angle *è* and distance *d*, will have values i and j respectively. When texture is coarse and *d* is small compared to the texture elements ("Speckle Pattern") then the pairs of points with distance *d* will have similar gray levels, so the points on the main diagonal of the matrices *p(i,j;d,è)* will have great values. On the other hand, if texture is smooth the values of the matrices will be more spread out. The features used in this algorithm are, Sum Entropy (SENT), Angular Second Moment (ASM), Inverse Difference Moment (IDM), Contrast(CON).

$$\text{SENT} = -\sum_{i=2}^{2N_g} p_{x+y}(i)\log\{p_{x+y}(i)\}\,,\ \text{ASM} = \sum_i\sum_j\{p(i,j)\}^2\,,\ \text{IDM} = \sum_i\sum_j \frac{1}{1+(i-j)^2}\,p(i,j)\,,\ \text{CON} = \sum_{i=1}^{N_g-1} n^2\,\{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\}$$

$j|=k$ $|i-$

where *Ng is number of gray levels,* ì$_x$ & ó$_x$ are the mean and standard deviation of the row sums of the matrix *p(i,j),* and ì$_y$ & ó$_y$ are the corresponding statistics of the column sums with p_{x+y} *and* p_{x-y} *given by:*

$$p_{x-y}(k) = \sum_{\substack{i=1\\|i-j|=k}}^{N_g}\sum_{j=1}^{N_g} p(i,j)\,, \qquad k=0,1,\ldots,N_g-1$$

Each measure was evaluated for d=1,2,3 and è=0^0,45^0,90^0,135^0; features were obtained from the sample mean and standard deviation of the estimated values.

v. *Fractal Dimension Texture Analysis (FDTA)*

The last technique used to quantify texture in images is based on the Fractional Brownian Motion (FBM) theory as presented by Mandelbrot. FBM is a nonstationary stochastic process which can be described by a single parameter, its fractal dimension D, where D is equal to E+1-H. The parameter H is the so-called Hurst coefficient and E+1 is the Euclidean dimension of the embedding space of the fractal. FBM and the corresponding D and H parameters can be used to describe the roughness of different surfaces. Mu et al. [3] have proposed that the use of the FBM model is suitable for the analysis of ultrasonic liver images. Similarly, we used the the Hurst coefficient for levels 32x32 (original region) H_5 and 16x16 H_4 to characterize ultrasonic liver images. The fractal dimension texture analysis (FDTA) is based on the fact that a rough surface gives a small value of H whereas a smooth surface gives a large value of H.

B. Fuzzy neural network classifier

We used a fuzzy neural network classifier to discriminate the three classes of images. The classifier creates fuzzy sets from the Voronoi diagram of the training patterns and builds class boundaries in a statistical manner [9]. The fuzzy neural approach considered here [9] creates fuzzy sets from the Voronoi diagram of the training patterns and builds class boundaries in a statistical manner. A Voronoi diagram, also known as Dirichlet tessellation or Thiessen polygon, is a partition of the pattern space into convex regions. Each of these regions contains points with minimum distance from a specific point (the region generator) compared to their distance from the other points used for the construction of the diagram.

Given a set of points in the feature space, the resulting Voronoi diagram can be viewed as a puzzle and the Voronoi regions as the pieces of this puzzle. We can assemble neighboring pieces according to their position and class, in order to appropriately specify the boundaries between classes. This formulation leads to a reduced Voronoi diagram where the new broader regions contain more than one adjoining Voronoi regions having the same class label (figure 2). The resulting aggregate regions are no longer convex and may be considered as fuzzy sets by defining membership functions indicating the degree of belongingness of points of the input space to each region. Each fuzzy set is characterized by a set of hyperplanes (separating the corresponding region from other regions) and a class label.

After constructing the fuzzy sets, decision probabilities are computed based on the density of membership values for each region and the respective performance in the selection of the correct region. Through discretization of the membership axis, a probabilistic function is created that establishes a correspondence between membership values in a specific region and the probability of correct classification. The construction of the probability models is based on the search for ranges of membership values that have more chance to lead to the successful selection of a region. More specifically, considering class region i, the interval [0,1] of membership values is divided into a number L_i of equal-size cells. To each cell v ($v=1, \ldots, L_i$) we assign a probability value p_i^v computed as the percentage of the training patterns belonging to region i that have their membership value in the cell v.

It should be observed that, after the membership values of training patterns to each region have been computed, it is possible to view the classification problem as mapping from the space of membership vectors to the set of classes, $c : (ì_1, \ldots, ì_R) \rightarrow \{1, \ldots, K\}$ (where R is the number of class regions and K is the number of classes). Such a mapping can be easily constructed using for example a multilayer perceptron trained by the backpropagation algorithm or any of its variants. Mapping the above procedure into a neural architecture we are able to obtain an algorithm for the design of fuzzy neural networks for pattern classification.

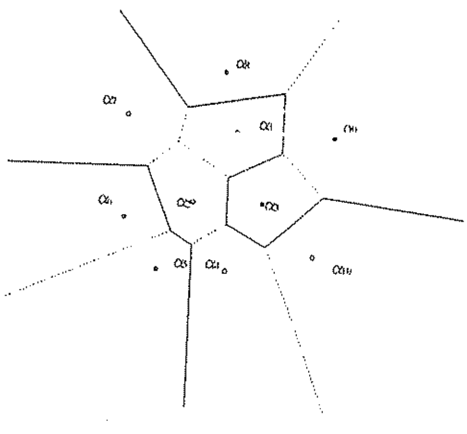
i. Neural Network Implementation

The proposed construction algorithm can be summarized into the following steps:

1. Construct the classical Voronoi diagram of a set of N patterns
2. $A = \{a_1, \ldots, a_N\}$, in a *d*-dimensional space.
3. Reduce the Voronoi diagram into a number of class regions.
4. Discard small class regions and let *R* be the number of the remaining large class regions.
5. For each pattern a_j, $j = 1, \ldots, N$, compute the membership values $\mu_i(a_j)$, $i = 1, \ldots, R$.
6. For each region i, $i = 1, \ldots, R$, categorize the membership values in a histogram using a number L_i of equal-size cells in [0,1].
7. Compute selection probabilities p_i^v, $i = 1, \ldots, R$, $v = 1, \ldots, L_i$.

In order to use the method for the classification of a new pattern, the membership values of the pattern to each region i are first computed. Then, the corresponding probabilities p_i^v are determined (where v represents the cell containing the membership value of the pattern) and the region i with maximum p_i^v is selected. The class of this region is considered as the final classification decision. The above decision approach can be implemented by means of a neural network architecture as illustrated in Figure 4. The architecture consists of five layers and connections exist only between successive layers. The first layer is the input layer having as many nodes as the dimension of patterns. The nodes in the second layer represent hyperplanes that define class regions. For each class region i there are $|H_i|$ nodes, one for each hyperplane supporting that class. As a hyperplane separates two regions, there will generally be two nodes referring to the same hyperplane (except for hyperplanes supporting small regions that were discarded during construction).

The third layer contains as many nodes as the number R of class regions. The output of each node i of this layer provides the membership value μ_i of the pattern to the corresponding region. The connections between nodes of the second and third layer assume binary values 1 or 0 to associate regions with their supporting hyperplanes. The fourth layer implements the membership histogram. Each region i of the third layer is connected to L_i nodes of the fourth layer corresponding to the cells of the histogram. Each such node v ($v=1, \ldots, L_i$) fires only in the case where the μ_i value falls inside the corresponding cell and provides the respective probability p_i^v, otherwise the output of the node is zero. This representation allows an efficient implementation of the histogram by means of simple nodes yielding a fixed output on an on-off basis. The fifth layer embodies one node for each of the K classes. If region i has class label k then the set of L_i nodes of the fourth layer (representing the histogram of region i) is connected to node k of the fourth layer. In other words, the connections between nodes of the fourth and fifth layer take binary values 1 or 0 to associate class regions (histogram cells) with class labels. The output ξ_k of each node k of the last layer is taken equal to the maximum of the outputs (probabilities p_i^v) of the cell nodes connected to that node. Finally, the class k with the maximum ξ_k is the decision of the fuzzy neural classification network.



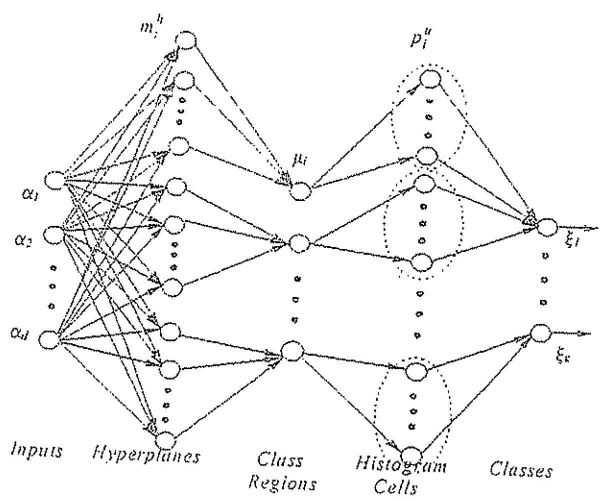


Figure 2: Schematic representation of class regions

Figure 3: Proposed neural network architecture

When a new pattern a is applied to the network, the membership values $\mu_i(a)$ of the pattern to each class region i are initially computed. The computation proceeds by determining the probabilities p_i^v corresponding to the respective histogram cells. The decision of the network is the class of the region with the maximum probability p_i^v, expressed by the quantity $\hat{i}_k$. As is the case with other neural network designs based on Voronoi diagram information [10,11,12], the method has the ability to completely define the neural structure, namely the number of hidden layers and nodes of each layer along with the connection values between nodes of successive layers. The proposed neural architecture incorporates an additional layer with respect to other approaches accounting for the computation of decision probabilities.

III. RESULTS

To evaluate the performance of the proposed computer assisted tissue characterization algorithm, we used a total of 150 images (Normal, fatty, and Cirrhosis). In the first phase, the twelve (12) texture analysis features described in Section II-A were calculated for all the images. As described previously, 32-by-32 pixels ROI were selected in each image and the corresponding texture features were calculated. These features have been shown to contain useful information for characterizing liver tissue pathology [10].

The second phase consisted of using the proposed fuzzy neural network classifier to discriminate liver abnormalities. For this, a set of 75 images (25 from each class) was used as learning set for the classifier, whereas another 75 images (25 from each class) were used as a test set. The performance of the classifier was then evaluated using different combination of classification features (image texture analysis features). Due to the large number of different subset combinations only those that resulted in correct classification accuracy rate of greater than 75% are presented in this study. To reduce the computational complexity in the training and classification process, we decided to limit the number of features used in the classification down to six. In that sense, combinations of six or less features (out of the 12 presented in section II-A) where used for the classifications. Table I shows the results of the proposed classifier in discriminating the different pathologies.

It is apparent that the proposed classifier provides high classification accuracy for all different pathologies. In particular the *<KYR, ASM, MEA, ASM, IDM, RP>* set achieves an overall 82.67% accuracy in characterizing the different pathologies, whereas individual accuracy is 80.00%, 88.00%, and 80.00% for Normal, Fatty and Cirrhotic liver respectively. Similar (although somehow lower) accuracy is obtained with two more feature sets of size six (accuracies of 80.00% and 78.67% respectively). All these figures are higher than those achieved by visual inspection by physicians that are approximately 70% for diffused liver diseases [4,5]. Furthermore, the proposed Fuzzy Neural Network classifier achieved higher accuracy in all cases than a conventional 1-Nearest Neighbor or K-NN classifier). In addition to that, the classification experiment verified the usefulness of the proposed image texture analysis features in discriminating liver tissue pathology from Ultrasound Images. Even subsets of texture features of size 5 (see Table I), were able to discriminate the different pathologies with accuracy higher than the 75% accuracy limit that we have set for the experiment. However, the reduced classification accuracy achieved with less than 6 features indicates that useful information is lost when a smaller feature set is used for classification. Due to the fact that the number of image texture features that were used in this experiment is only part of the image texture features available, we can easily understand the possibilities the proposed methodology offers in computer-assisted diffused liver disease characterization.

IV. CONCLUSIONS

Computer assisted characterization of ultrasonic liver images using image texture analysis techniques and fuzzy classifiers has been tested and evaluated. In particular, we have implemented a neural network classifier that is based on geometrical fuzzy sets. The approach is based on the construction of Voronoi diagrams in the pattern space and the creation of region aggregates inside the Voronoi puzzle. For the constructed class regions, decision probabilities are computed in terms of the distribution of membership values to these regions. The whole technique can be implemented by means of a five-layer feed-forward neural network architecture.

Experimental results indicate that the proposed method is effective in terms of the rate of correct classification and has the ability of overcoming the difficulties arising from the problem of overlapping classes. Moreover, it has the characteristic of maintaining the powerful geometrical features of the Voronoi structure as well as of creating efficient decision boundaries through the statistical processing of membership values. This work allows us to further experiment with the use of proximity based approaches to the construction of fuzzy neural classifiers and to discover more efficient techniques in the area of soft decision making. Since the complexity of the construction of Voronoi diagrams becomes high as the dimension of the feature space grows, we are interested in applying effective geometrical algorithms that can suggest neighbors of a given pattern (in the sense of the Voronoi diagram) for large dimensional problems.

TableI: Fuzzy Neural Network Classifier correct classification rates.

Feature set (features presented in Section II-A)	Normal	Fatty	Cirrhosis	Total
FOP_KUR, GLD_ASM, GLD_MEA, SGLD_ASM, SGLD_IDM, RUNL_RP	80.00%	88.00%	80.00%	82.67%
GLD_ENT, SGLD_SENT, SGLD_CON, RUNL_SRE, FDTA_H4, FDTA_H5	76.00%	84.00%	80.00%	80.00%
FOP_KUR, GLD_ASM, SGLD_SENT, SGLD_IDM, RUNL_RP, FDTA_H4	80.00%	80.00%	76.00%	78.67%
FOP_KUR, GLD_ASM, GLD_MEA, SGLD_ASM, RUNL_RP	76.00%	84.00%	68.00%	76.00%

Furthermore, the results of this work have demonstrated the ability of using image texture analysis technique to extract features that characterize liver tissue abnormalities. The proposed features, when combined in a feature set of size 6, achieved a higher classification accuracy than that reported for physicians in diffused pathologies and than those obtained by Nearest Neighbor classification. Furthermore, the fact that a feature set of size 6 obtained higher accuracy than all subsets of features of size 5 or less, indicates the feature complimentarity in characterizing the pathologies involved.

Concluding, we should point out that an ultrasonic image depends on many factors, and characterizing ultrasonic images is not a trivial task. Initial results proved to be very promising. Furthermore, we expect that further evaluation of the techniques using larger image data set and the incorporation of additional algorithms will be able to improve the overall accuracy of the method.

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