**Fuzzy similarity measures for ultrasound tissue characterization**

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## ABSTRACT

Computerized ultrasound tissue characterization has become an objective mean for diagnosis of diseases. it is difficult to differentiate diffuse liver diseases, namely cirrhotic and fatty liver from normal one by visual inspection from the ultrasound images. The visual criteria for differentiating diffused diseases is rather confusing and highly dependent upon the sonographer experience. The need for computerized tissue characterization is thus justified to assist quantitatively the sonographer for accurate differentiation and to minimize the degree of risk from erroneous interpretation. In this paper we used the fuzzy similarity measure as an approximate reasoning technique to find the maximum degree of matching between an unknown case defined by a feature vector and a family of prototypes (knowledge base). The feature vector used for the matching process contains 8 quantitative parameters (Textural, acoustical, and speckle parameters ) extracted from the ultrasound image. The steps done to match an unknown case with the family of prototypes (Cirr, Fatty, Normal) are: Choosing the membership functions for each parameter, then obtaining the fuzzification matrix for the unknown case and the family of prototypes then by the linguistic evaluation of two fuzzy quantities we obtain the similarity matrix, then by a simply aggregation methods and the fuzzy integrals we obtain the degree of similarity. Finally we find that the similarity measure results are comparable to the neural network classification techniques and it can be used in medical diagnosis to determine the pathology of the liver and to monitor the extent of the disease.

## 1. INTRODUCTION

Pulsed-echo ultrasound is a non-invasive technique capable of visualizing an internal structure of soft tissues and as such it is considered to be an extremely important and valuable tool of medical diagnosis. The physician has rely on detection of inhomogeneities between echo amplitudes received from the neighboring areas of the image. Such an approach is, of course, subjective and consequently problematic in itself. Moreover, in certain cases the disease attacks the entire tissue area, say, entire liver (diffuse liver diseases). Then, the ultrasonic image will be homogeneous (see figure 1), and as a result the diagnosis is sometimes difficult[1-8].

Visual criteria for diagnosing diffused liver diseases are in general confusing and highly subjective because they depend on the sonographer to observe certain textural characteristics from the image and compare them to those developed for different pathologies to determine the type of the disease. Moreover, some of the diseases are highly similar in their diagnostic criteria, which tend to confuse the sonographers even more.
The quantitative analysis of using ultrasound signals as an aid to the diagnosis of diffuse disease has been described by many researchers[2-7, 9-20].

The field of fuzzy logic[21,22] and fuzzy similarity[28,30,34,35] measure and it's application in object matching is an active area of research. Many techniques of pattern matching are developed using fuzzy logic and the approximate reasoning. Mixed systems of neural network and fuzzy logic have also developed [29] for a wide range of applications. Very often, one is faced with a nontrivial case of partial matching, matching that returns with a degree of matching lying in a unit interval. In matching procedures, a concept of similarity is a significant one. As said previously, the matching procedure implies a degree of matching reached for two fuzzy quantities. Unfortunately, nothing is known about certainty (or uncertainty) of the result obtained. We start with recalling some measures that are used for matching purposes. The main role of this section is to underline some of their characteristic features and highlight existing shortcomings.


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## 2. MEASURES OF EQUALITY BETWEEN TWO FUZZY QUANTITIES

In this section, we will summarize some existing approaches that are useful for determination of a degree of equality (degree of matching) for two fuzzy quantities. Let us focus our attention on the comparison of two fuzzy sets A and B defined in the same universe of discourse X, say A, B: $X \rightarrow [0,1]$.

### 2.1 Distance Measure

A board class of measures of equality is based on distance measure. Usually, a general form of Minkowski r-metric is given as:

$$d_n(A, B) = \left( \int_{-\infty}^{\infty} |A(x) - B(x)|^r \, dx \right)^{1/r} \qquad r \geq 1 \tag{1}$$

### 2.2 Set-Theoretic considerations

The second class of measures of equality originates from some basic set-theoretic considerations.

- Based upon the dissimilarity measure defined as the ratio
  $\text{Card}(A \cap B) / \text{Card}(A \cup B)$ (2)
- Possibility measure of two fuzzy sets. The measure describes the highest degree to which these two fuzzy quantities A and B overlap,

$$\pi(A, b) = \sup_{\chi \in X} [\min(A(x), B(x))] \tag{3}$$

### 2.3 Logical framework.

The third way of dealing with the comparison of two fuzzy quantities is performed in a logical framework. One among well-known approaches in this group refers to linguistic evaluation of two fuzzy quantities that leads directly to notions of fuzzy logic ( a so-called fuzzy truth values). For a certain element of the universe of discourse X a degree of equality [34] of a and b, a, b, $\in [0,1]$ is equal to

$$a \equiv b = \left\{ (a \rightarrow b) \wedge (b \rightarrow a) + (\bar{a} \rightarrow \bar{b}) \wedge (\bar{b} \rightarrow \bar{a}) \right\} \tag{4}$$

Here $\wedge$ stands for minimum, $\rightarrow$ forms an implication[22] and $\bar{a} = 1-a$. Then applying conjunctions known in fuzzy sets, the aforementioned formula is translated into the form plausible for computational purposes. Simply speaking the implication $\rightarrow$ is modeled by various pseudo complements induced by corresponding t-norms[22] e.g., for the t-norm specialized as minimum reads as

$$a \equiv b = \begin{cases} (1 + b - a) & \text{if } a > b \\ 1. & \text{if } a = b. \\ (1 + a - b) & \text{if } a < b \end{cases} \tag{5}$$

For another t-norm specialized as product we get

$a \rightarrow b = \min(1, b/a)$

and finally

$$a \equiv b = [(a \rightarrow b)(b \rightarrow a) + ((1-a) \rightarrow (1-b))((1-b) \rightarrow (1-a))]$$

$$= \begin{cases} [b/a + (1-a)/(1-b)], & \text{if } a > b \\ 1. & \text{if } a = b. \\ [a/b + (1-b)/(1-a)], & \text{if } a < b \end{cases} \tag{6}$$

The last method of matching of two fuzzy quantities is closely related to an essence of computations with fuzzy sets. Therefore, in further discussion we will concentrate ourselves on studies on the equality index as given by method 3.

Additionally this third approach enables us to perform a point wise matching process. In the case of the third type of these measures it is sometimes of interest to have a mechanism within which one combines the grades of equality to get a single number specifying an overall characterization of equality of the fuzzy set. At least four basic methods are often utilized and we will add to this list the fuzzy integrals method and we will discuss it later.

- A maximal value among the degree of equality is taken
- A maximal value of the degrees of equality is considered.
- Averaging way of aggregation; degrees of equality are averaged.
- Fuzzy integrals method[33,35].

Each of the previously listed methods of aggregation leads to a point characterization. A significant amount of information is lost. Therefore, it is of interest to aggregate them accordingly to particular application needs.

### 2.4 Fuzzy measure

When we consider a certain set X, the function g that makes subset E and F correspond to the values in the interval [0,1] are called fuzzy measures[35] if they have the following properties:

(1) $g(\varnothing) = 0,\ g(X) = 1$ (7)

(2) If $E \subset F,\ g(E) \leq g(F)$ (8)

(3) If $E_1 \subset E_2 \subset \ldots$ or $E_1 \supset E_2 \supset \ldots$ $\lim_{n\to\infty} g(E_n) = g\left(\lim_{n\to\infty} E_n\right)$ (9)

### 2.5 Fuzzy integrals

The fuzzy integral[33,35] of function $h:\ X \to [0,1]$ on $E \subset X$ by fuzzy measure g is defined as follows:

$$h(x) \circ g = \max_{E \subset X}\left[\min_{x \in E}\left(h(x)\right) \wedge g(E)\right]. \tag{10}$$

## 3. PROPOSED METHOD FOR PATTERN MATCHING

Many technique for pattern matching and classification using fuzzy logic has been proposed , and now used in many application such as speech[30] and character recognition's, medical diagnosis[23-27] and decision making . In the following paragraph we will introduce a proposed method for medical diagnosis based on the similarity measure of the unknown case and the sets of a prototypes from a known cases.

Give a vector $X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$

where n in the dimension of the vector X and the number of the classification parameters ( features) in the system.

$x_i$ denotes the measured ith feature of the event, and X represented as a point in n dimension vector space $\Omega_X$ consisting of m ill defined pattern classes $C_1, C_2, .., C_i, .. C_m$ let $R_1, R_2, ... R_i, ..., R_m$ be the reference vectors where $R_i$ associated with $C_i$ containing $h_i$ number of prototypes such that .

$$R_j^{(l)} \in R_j \quad l = 1,2,...h_j \tag{11}$$

The pattern X can then be assigned to be member of that class if it shows maximum similarity to this class.

### 3.1 Fuzzification process.

Assume each feature as a linguistic variable has a number of fuzzy values e.g. High, Med, Low, and all the linguistic variables has the same number of fuzzy values. The fuzzification is done by getting the value of the membership functions, so obtaining a fuzzification matrix .

$$\aleph = \text{Fuzz}(X) = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & x_{ij} & & \\ & & \vdots & & \\ x_{z1} & & & & x_{zn} \end{bmatrix} \tag{12}$$

where z is the number of the linguistic values for the linguistic variables and

$$x_{ij} = F_{ij}(x_i) \tag{13}$$

where $F_{ij}$ is the membership function of the linguistic value i for the fuzzy value j.

We do the fuzzification as described above for the X and all Rj.

**3.2 Similarity Measures**

So the problem how to measure the similarity between $\aleph$ and $R^l_j$ and obtain the over all similarity of this X and the other classes $C_j$ represented by the $R_j$ prototypes. As described in the previous sections that many technique can be used as , distance measure , from fuzzy set theories , linguistic evaluations. We will use the linguistic evaluation of two fuzzy quantities.

$$a \equiv b = \frac{1}{2}\{(a \to b) \wedge (b \to a) + (\bar{a} \to \bar{b}) \wedge (\bar{b} \to \bar{a})\} \tag{14}$$

if the implication chosen min so the above equation can be red as:

$$a \equiv b = \begin{cases} (1 + b - a) & \text{if } a > b \\ 1 & \text{if } a = b. \\ (1 + a - b) & \text{if } a < b \end{cases} \tag{15}$$

so given $\aleph$, Fuzz($R^l_j$) = $R^l_j$ by using the linguistic evaluation obtain the similarity matrix $S^l_j$.

$$\aleph = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & x_{ij} & & \\ & & \vdots & & \\ x_{z1} & & & & x_{zn} \end{bmatrix} \tag{16}$$

$$R^l_j = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & r_{ij} & & \\ & & \vdots & & \\ r_{z1} & & & & r_{zn} \end{bmatrix} \tag{17}$$

$$S_j^l = \begin{bmatrix} s_{11} & \cdots & s_{1j} & \cdots & s_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & s_{ij} & & \\ & & \vdots & & \\ s_{z1} & & & & s_{zn} \end{bmatrix} \tag{18}$$

where

$$s_{ij} = \; x_{ij} \equiv r_{ij} \tag{19}$$

Two methods can be used to get the similarity index between the ℵ and $R_j^l$.

The first is to obtain the similarity vector H as follow:

$$\mathrm{H}_j^l = \left[\frac{1}{z}\sum_z f(s_{z1})\cdots\frac{1}{z}\sum_z f(s_{zn})\right] = [\mathrm{h}_1 \ldots \mathrm{h}_n] \tag{20}$$

where f is a suggested function for re-waiting the linguistic evaluation, its' effect to increase the wait of the similar values and decrease the wait for dissimilar values. The f function could be any function to increase the degree of the similarity if it exceeds a certain threshold, or to decrease the wait of this number if the linguistic evaluation is less a certain threshold. Many function can be used to do this mission, such as,

a) Sigmoid function

$$f(\alpha) = \frac{1}{1 + e^{-(\alpha - \theta)}} \text{ where } \theta \text{ is the selected threshold.} \tag{21}$$

b) Hard threshold

$$f(\alpha) = \begin{cases} 1 & \text{if } \alpha \geq \theta \\ 0 & \text{if } \alpha < \theta \end{cases} \tag{22}$$

c) S function

$$S(u) = \begin{cases} 0 & u \leq \alpha \\ 2[(u-\alpha)/(\gamma-\alpha)]^2 & \alpha \leq u \leq \beta \\ 1 - 2[(u-\gamma)/(\gamma-\alpha)]^2 & \beta \leq u \leq \gamma \\ 1 & u \geq \gamma \end{cases} \tag{23}$$

obtain the similarity index $S_j^l$

$$S_{H_j}^l = \frac{1}{n}\sum_n h_n \tag{24}$$

which represents how similar is this unknown case to the category j, prototype $l$.

The second method by using the fuzzy integral. Where $h$ represents the similarity function and g represents a simple fuzzy measure which is the cardinality of the set $E$, $E \in X$ and $X$ is the power set of the X.

$$hg = h(x) \circ g = \max_{E \subset X}\left[\min_{x \in E}\big(h(x)\big) \wedge g(E)\right]. \tag{25}$$

If we apply the fuzzy measure described before to the $S_j^l$ rows

$$S_j^l = \begin{bmatrix} R_1 \\ \vdots \\ R_z \end{bmatrix} \text{ where } R_i = \begin{bmatrix} s_{1l} & \cdots & s_{ni} \end{bmatrix}. \quad (26)$$

$$HG_i^l = \begin{bmatrix} hg_1 \\ \vdots \\ hg_z \end{bmatrix} \quad (27)$$

where $hg_i$ is the fuzzy integral of the row i in the $S_j^l$ matrix.

### 3.3 Aggregation methods

Many criteria can be selected to get the similarity between X and the category j, such as follows.

a) $S_j = \max_l \ S_j^l$ (28)

b) $S_j = \min_l \ S_j^l$ (29)

c) $S_j = \frac{1}{l}\sum_l S_j^l$ (30)

note that $S_j^l$ can be $S_{G_j}^l$ or $S_{H_j}^l$

## 4. ULTRASOUND IMAGE ACQUISITION AND FEATURES EXTRACTION

In the data acquisition system, the video output of a Kretz-320 mechanical sector ultrasound scanner was connected to a Matrox PIP-512 frame grabber card on an IBM-386 PC. The image is captured in 512X512 pixels, the resolution is 8 bits/pixel. A s/w was developed to define the *ROI* and to extract all the aforementioned parameters (image analysis)[12-15,19,20].

To obtain a reproducible results, the following parameters were standardized for all tissue characterization parameters[19,20]:

1-**Ultrasound machine settings:** e.g., TGC, FOCUS, FREQUENCY, and ZOOM controls, which can change the overall image gain and produce zooming effects and hence deviates the image statistics in an unpredictable way. Moreover, the frequency of ultrasound waves used must be the same since the attenuation is frequency dependent.
2-**ROI shape and size:** to obtain a reliable statistics, the number of pixels in the ROI must be at least 1000 pixels (32 pixel per centimeter). The shape of the box is taken to be square.

### 4.1 Quantitative features

The quantitative parameters measured for ultrasound tissue characterization are four broad categories extracted from pulse-echo data (gray scale B-mode image). There are more than 40 different parameters that extracted from the pulse echo data and are correlated with the pathology of the case. Among these 40 different parameters we used 8 significant parameters from the four broad categories. The categories of parameters are:

***1-Image textural parameters:***
These are mean gray level (*MGL*), gray level variance (*VAR*), and five of the relevant gray level histogram *percentiles*. Co-occurrence matrix parameters, such as contrast (*CON*), entropy (*ENT*), correlation (*COR*), and angular second moment (*ASM*)[10].

***2-Speckle Parameters:***

These are mean scatterer separation ($d$), diffuse and specular scatterer intensity ($I_d, I_s$), specular standard deviation $\sigma_s$ ) and a few other related parameters[16].

***3-Radiofrequency parameters:***

These are attenuation coefficient ($ATTEN\ \alpha$) and the backscattering coefficient ($BSC\ \mu$)[2,5,7,16,17].

***4-Autoregressive parameters:***

These are normally 6X6 autoregressive model matrix for the selected region of interest (*ROI*, normally 50X50 pixels)[18]. The sum of all these parameters may exceed 40 but the most significant parameters used for classification are 8. These parameters were evaluated using correlation measurements in order to have a reduced set of uncorrelated parameters, and to mark those parameters which correlate the strongest to the different pathologies[12-5,19]. These 8 parameters are mean gray level (*MGL*), first percentile (*PER0.1*), contrast (*CON*), entropy (*ENT*), correlation (*COR*), angular second moment (*ASM*), attenuation coefficient ($ATTEN\ \alpha$), and scatterer separation ($d$).

The clustering of the three pathologies was previously done using statistical methods ($k$ nearest neighbor)[9], neural networks (both functional neural network[14,15], and category learning network[13,19]) and Fuzzy logic by using fuzzy rules[31,32].

**4.2 Features membership functions type and selection**

Assume the domain intervals for each parameter , where the domain interval of a variable means that most probably this variable will lie in this interval (the value of the variable is allowed to be outside this domain). Divide each domain interval into three regions denoted by *High, Low,* and *Med.* Assign each region a certain fuzzy membership function. We have chosen three forms of membership functions the first is the triangle form, the second is the trapezoidal form and the third is bell form. The equation of the bell form used in the analysis is as follow:

$$\mu_S(s) = e^{-[(s-\bar{s})^2/2\sigma^2]} \tag{31}$$

where $\mu_s$ denotes the membership function of a fuzzy value. Choosing the fuzzy singleton $\bar{s}$ ) for each fuzzy set depends on two criteria: 1- statistical basis. 2- expert knowledge. The bell form of the membership function given above is taken for the fuzzy value *Med.* For the *Low* value if $s < \bar{s}$ then $\mu_s$ equals to 1. For the *High* value if $s > \bar{s}$ then $\mu_s$ equals to 1.

Since we have only three pathologies and the size of the input space is 8, we have chosen only three regions for each variable because the high resolution is not required in this case to take a decision. The epsilon-completeness[22] is chosen to be equal to the crossover point as shown in figure 2. In this sense a dominant rule always exists and is associated with the degree of belief greater than 0.5. The output which is a linguistic variable called the pathology, has three fuzzy values named Normal, Fatty and Cirrhosis.

## 5. RESULTS AND DISCUSSIONS

The image is quantitatively analyzed for the 8 significant parameters. A needle *BIOPSY* is obtained for every patient. The decision was made based on the history information, laboratory, pathological (*BIOPSY*), clinical measurements, and clinician experience. The aforementioned protocol was done for a set consisting of greater than 140 cases for the three pathologies: Normal, Fatty, and Cirrhotic livers.

The total number of cases used is greater than 140 cases (we acquire images for patients if it is fully clinically and pathologically investigated) for the three classes. Each class contains approximately 40 cases.
Using the fuzzy similarity techniques described above to get the degree of similarity between an unknown case represented by the vector X in the 8-dimensional space (the number of parameters) and the sets of prototypes. We have tested the

system using cases greater than 40 unknown cases and the technique showed a very good results that match up with the clinical and pathological investigations (*BIOPSY*).

If we found a high similarity between the test cases that are fully investigated and the family of prototypes, we append this case to the prototypes family. If the case is fully investigated, it is appended directly to our prototypes.

The results of this work revealed the potential value for considering the idea of fuzzy similarity measures in tissue characterization of diffused liver diseases (we can apply this for most of the soft tissues that their diffuse diseases are confusing like liver, spleen and kidney diseases). This potential value could be used for an on-line diagnosis of the pathology, and minimize the risk of taking needle Biopsy from the patient. The results of this work was compared to the other techniques used for tissue classification as statistical similarity[9], neural network[13,14,15], fuzzy logic rules methods[31,32] and the results showed an excellent results for correct diagnosis.

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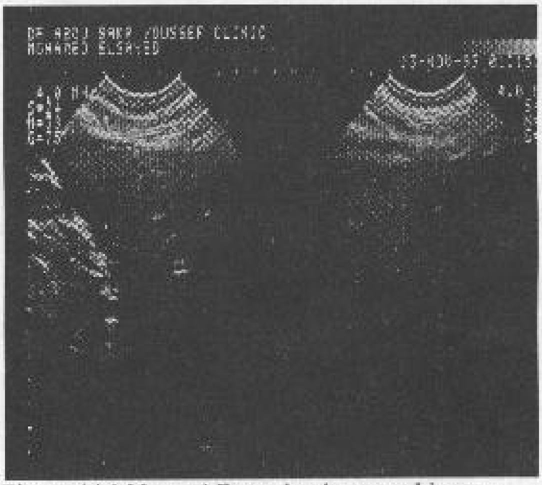

Figure 1(a) Normal B-mode ultrasound image

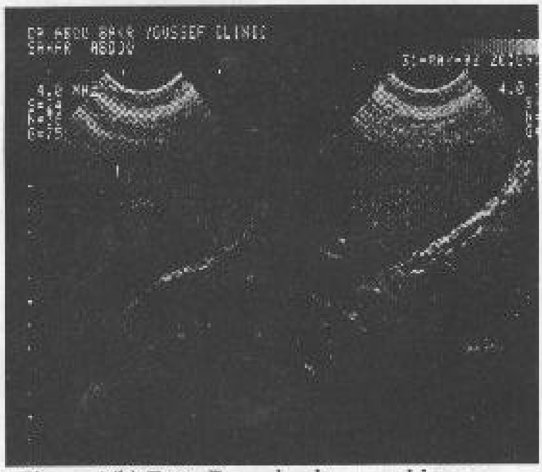

Figure 1(b) Fatty B-mode ultrasound image

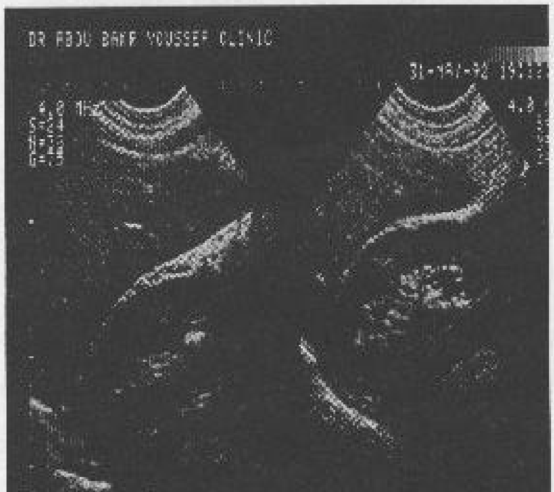

Figure 1(c) Cirrhotic B-mode ultrasound image

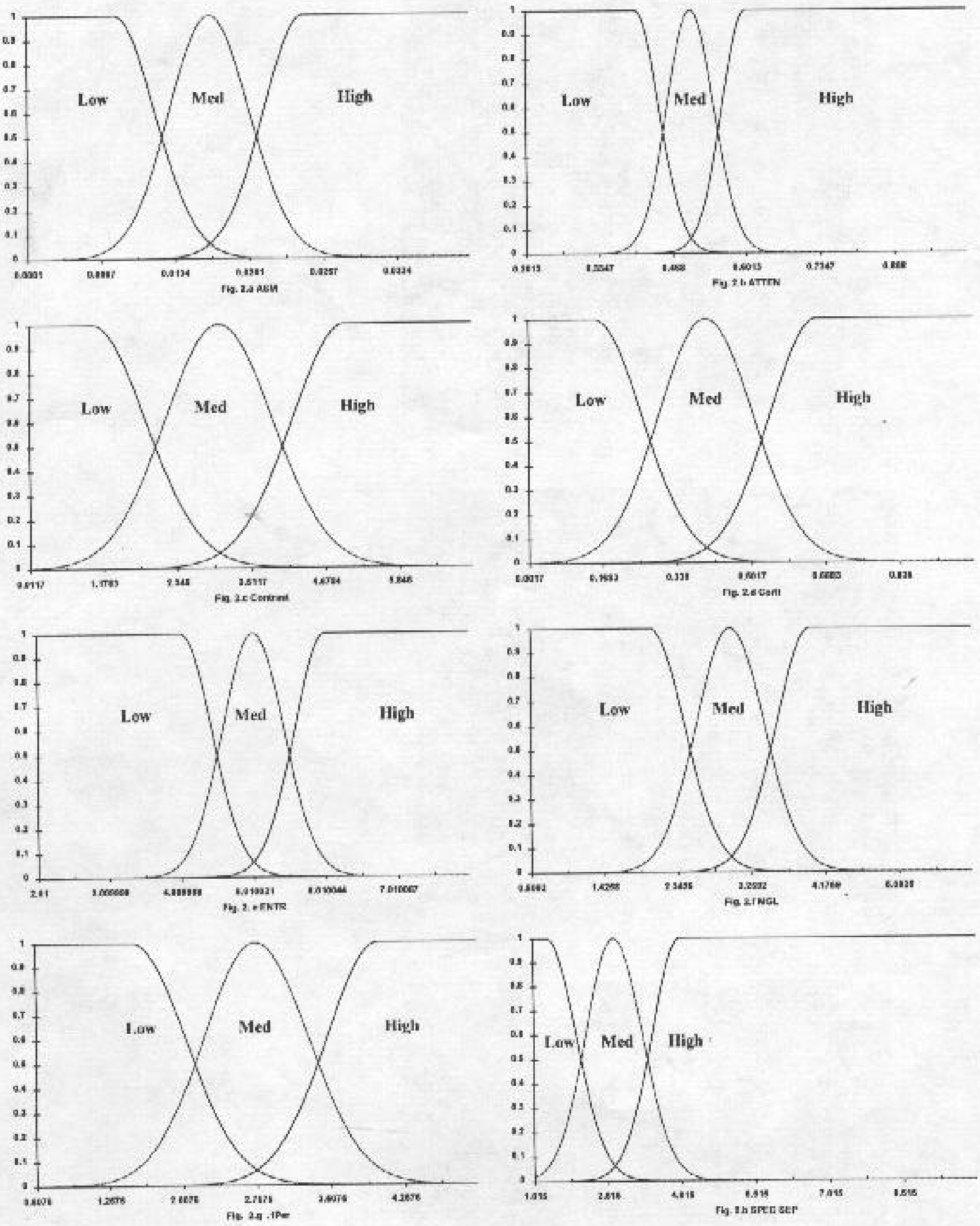


Figure 2: All the membership functions for all the parameters used in the analysis