ULTRASOUND TISSUE CHARACTERIZATION OF DIFFUSE LIVER DISEASES USING FUZZY RULES

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Abstract. Computerized ultrasound tissue characterization has become an objective mean for diagnosis of liver diseases. It is difficult to differentiate diffuse liver diseases, namely Cirrhotic and Fatty liver by visual inspection from the ultrasound images. The visual criteria for differentiating diffused diseases is rather confusing and highly dependent upon the sonographer experience, this often causes a bias effects in the diagnostic procedure and limits its objectivity and reproducibility. The need for a computerized tissue characterization is thus justified to assist quantitatively the sonographer for the accurate differentiation and to minimize the degree of risk from erroneous interpretition. Fuzzy logic has emerged as one of the most active area in classification. In this work we present an approach that employs fuzzy reasoning techniques to automatically differentiate diffuse liver diseases using numerical quantitative features measured from the ultrasound images. Fuzzy rules were generated for over 120 cases of Normal, Fatty and Cirrhotic livers. The input to the fuzzy system is a vector of dimension (8), and contains the *MGL*, the *PER0.1*, the *CON*, the *ASM*, the *ENT*, the *CORR*, the *ATTEN* and the speckle separation($\bar{d}$). The output of the fuzzy system is the category of pathology either Cirrhosis, Fatty or Normal.
The steps done for differentiating the pathologies are, data acquisition, feature extraction, dividing the I/O spaces of the measured quantitative data into fuzzy sets based on the expert knowledge, generating the fuzzy rules using the fuzzy inference procedures to determine the pathology. In this work different membership functions are assigned for the input spaces. Finally fuzzy logic presented a good accuracy for classifying different diffused liver pathologies. This classification technique can be of value in tissue signature.

Keywords. Tissue Characterization, Liver, Diffuse Disease, Feature Extraction, Ultrasound Parameters, Fuzzy Logic.

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. However, despite their importance, existing ultrasonic systems have a number of important shortcomings. The main problem stems from the fact that presently the diagnosis is, usually, of qualitative nature. 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. An example for these features is texture homogeneity. Its presence or absence can be widely debated between different experienced sonographers. Another feature is texture echogenicity which can be a matter of argument in marginal cases. Moreover, some of the diseases are highly similar in their diagnostic criteria, which tend to confuse the sonographers even more.

The Visual criteria provides low diagnostic accuracy (around 70%) [1,9,10,18-20]. Therefore the physicians may have to use further invasive methods such as the pathology investigation of ultrasonically guided needle Biopsy. Although this technique is considered to be the golden test for diagnosis, it has the disadvantage of being invasive and more importantly, it may cause a great risk of cancer spread if it cuts through a localized cancer area [9-12]. 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 quantitative parameters measured for ultrasound tissue characterization are four broad categories extracted from pulse-echo data (gray scale B-mode image). These 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 (σ_s) and a few other related parameters [16].

3-Radiofrequency parameters: These are attenuation coefficient (*ATTEN*) and the backscattering coefficient (*BSC*) [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 [12-15,19]. 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*), and scatterer separation (*d*). The clustering of the three pathologies was previously done using statistical methods (*k* nearest neighbor) [9], and neural networks (both functional neural network [14,15], and category learning network [13,19]).

DATA ACQUISITION

In the DAS 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 forementiond 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, size and *location:* to obtain a reliable statistics, the number of pixels in the *ROI* must be at least 1000 pixels, the shape should be square. To avoid the distorting effects in an ultrasonic wave patterns such as side lobes and grating lobes, the *ROI* is selected at the center line of the image, and then corrected for diffraction and focusing of the ultrasound beam.

MATERIALS AND METHODS

The B-mode images are acquired at *4-Mhz*, digitized, and corrected for diffraction and focusing. Then 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 measurements, clinical biopsy, and clinician experience.

This protocol was done for a set consisting of greater than 120 cases for the three pathologies: Normal, Fatty, and Cirrhotic livers [12-15,19]. The set of data was divided into two sets, one set to derive the fuzzy rules while the other to test the performance of the system based on the previously generated rules.

Fuzzy logic provides an algorithm which can convert the linguistic rules into decision strategy [21,22,28,29]. In fuzzy logic the decision is based on a set of linguistic description rules based on expert knowledge. From this set of rules, the inference mechanism will provide a linguistic decision.

The ***GMP*** (generalized modus ponens) plays an important role in this process. The simplest form of ***GMP*** is

primes 1: x is A'

primes 2: IF x is A THEN y is B

consequence: y is B'

where A, B, A', B' are fuzzy sets and x, y are linguistic variables. Several methods of inference mechanisms are based on this form of approximate reasoning. The most important inference mechanism is the compositional rule of inference suggested by Zadeh [21]. The general form of this compositional operator is denoted by sub star composition [22]. $y = x \circ R$, where $\circ$ presents the compositional operator and R is a fuzzy relation represented by any fuzzy implication function. The fuzzy rule in the form of "***IF*** x is *A and* y is *B* ***THEN*** z is *C*", is a fuzzy relation R defined as follow:

$$\mu_R \triangleq \mu_{(A \text{ and } B \to C)}(u,v,w) = [\mu_A(u) \text{ and } \mu_B(v)] \to \mu_C(w)$$

Where "A and B", are fuzzy sets $A \times B$ in $U \times V$ and $R \triangleq (A \text{ and } B) \to C$ is a fuzzy implication in $U \times V \times W$.

Nearly 40 distinct fuzzy implication functions have been described in literature [22]. The most well-known fuzzy implication function is described by Mamdani and Larsen.

In the recent years many techniques of medical diagnosis has prompted attempts to model the relation between the diseases and symptoms by using fuzzy logic. Many approaches in this field has been proposed [23-27]. In the field of medical imaging there is an uncertainty found in the process of diagnosis of diseases, especially in ultrasound diagnosis of diffused diseases using the visual criteria [12,13,18-20].

In our approach the medical knowledge is represented by a fuzzy relation R between the ultrasound characteristic features and pathologies, thus given the fuzzy set S of the measured features calculated from the ultrasonic image then the fuzzy set D of possible pathology can be inferred by the compositional rule of inference, $D = S \circ R$.

In our case the fuzzy relation R is a fuzzy rules extracted from a numerical data by the method suggested by L. Wang and J. Mendel [30]. For each ultrasonic image , the image is quantitatively analyzed for the 8 significant parameters described above. A needle biopsy is obtained for every patient. The decision was made based on the history information, laboratory measurements, clinical ,biopsy and clinician experience. The data sets consisted of 140 sets for the three pathologies *Normal*, *Fatty*, and *Cirrhotic* livers. So we have a set of 140 I/O pairs in the form of $((MGL_i, PER0.1_i, CON_i, ENT_i, COR_i, ASM_i, ATTEN_i, d_i), PATH_i)$ where i runs along all the cases.

Some of the selected parameters are scaled, these parameters are MGL, PER0.1, CONT. The MGL is based on 256 greyscale and the MGL value is divided by 5, and so as PER0.1 value. The CON value is divided by 8.

Example for Fatty pathology: ((*MGL=2.6, PER0.1=1.6, CON=1.313, ENT=5.113, COR=0.682, ASM=0.0084, ATT=0.7782, d=1.44*), *Fatty*).

Example for Normal pathology: ((*MGL=3.75, PER0.1=2.8, CON=2.304, ENT=5.1, COR=0.1899, ASM=0.008, ATT=0.511, d=1.6*), *Normal*).
Example for Cirrhosis pathology: ((*MGL=3.9, PER0.1=2.8, CON=4.2, ENT=5.53, COR=0.1648, ASM=0.00585, ATTEN=0.5814, d=2*), *Cirrhosis*).

***Rules extraction steps*:**

step 1. Assume the domain intervals for each parameter ,where the domain interval of a variable means that most propably 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

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

where μ_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 μ_S equals to 1. For the *High* value if $s > \bar{s}$ then μ_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 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.

step 2. First determine the membership degrees for each of the given parameters $MGL_i, PER0.1_i, CON_i, ENT_i, COR_i, ASM_i, ATT_i$ and d_i in all the different regions . For example MGL_1 has degree 0.8 in *High* ,0.3 in *Med* and 0.09 in *Low*. Then we assign the maximum degree of the three to the given parameter i.e MGL_1 is *High* . Finally obtain a rule from one pair of desired input-output data. e.g the rule generated for the data
((*MGL=2.6, PER0.1=1.6, CON=1.313, ENT=5.113, COR=0.682, ASM=0.0084, ATT=0.7782, d=1.44*), *Fatty*) has the form
IF ((*MGL* is *Med*) *and* (*PER0.1* is *Low*) *and* (*CON* is *Low*) *and* (*ENT* is *Med*) *and* (*COR* is *High*) *and* (*ASM* is *Low*) *and* (*ATTEN* is *High*) *and* (*d* is *Low*)) ***THEN*** pathology is Fatty.

step3. Rules validation, since there are a lot of data pairs, every pair generates one rule, it is probable that there will be some conflicting rules, i.e., rules that have the same ***IF*** part but have different ***THEN*** part. In our case there are no conflicted rules reported since there are parameters that are too separable along the categories. The value of these parameters are not probable to lie in the range of the other categories.

Inference Mechanism

The inference mechanism used was based on *SUP. MIN* compositional rule of inference .
The generated rules from the data are as follow:
R_1: ***IF*** ((*MGL* is *Med*) *and* (*PER0.1* is *Low*) *and* (*CON* is *Low*) *and* (*ENT* is *Med*) *and* (*COR* is *High*) *and* (*ASM* is *Low*) *and* (*ATTEN* is *High*) *and* (*d* is *Low*)) ***THEN*** pathology is Fatty.
also
R_2: ***IF*** ((*MGL* is *High*) *and* (*PER0.1* is *Med*) *and* (*CON* is *High*) *and* (*ENT* is *Med*) *and* (*COR* is *Low*) *and* (*ASM* is *Low*) *and* (*ATTEN* is *High*) *and* (*d* is *Med*)) ***THEN*** pathology is Cirrhosis.
also
R_3,....., R_n ,where n is the number of the generated rules. The connective *and* is commonly used as the *min* operator, while the connective *also* defined as the *union* operator. The firing strength for each rule is as follows :

$$\alpha_{R_i} = \mu_{MGL_{Ri}}(mgl) \wedge \mu_{PER.1_{Ri}}(per.1) \wedge \mu_{CON_{Ri}}(con) \wedge \mu_{ASM_{Ri}}(asm)$$

$$\wedge \mu_{COR_{Ri}}(cor) \wedge \mu_{ENT_{Ri}}(ent) \wedge \mu_{ATTEN_{Ri}}(atten) \wedge \mu_{d_{Ri}}(d)$$

where i runs along all the cases, $\wedge$ is the minimum operator. For each class of the three pathologies, we use the *max* operator for the firing strength corresponding to this class.
$\alpha_{Fatty} = max(\alpha_{Fi})$ where α_{Fi} denotes the firing strength generated from the rules that have a fatty output, i runs along all the Fatty cases.
$\alpha_{Cirrhosis} = max(\alpha_{Ci})$ where α_{Ci} denotes the firing strength generated from the rules that have a Cirrhotic output, i runs along all the Cirrhotic cases.
$\alpha_{Normal} = max(\alpha_{Ni})$ where α_{Ni} denotes the firing strength generated from the rules that have a normal output, i runs along all the Normal cases.
$\alpha_p = max(\alpha_{Normal}, \alpha_{Fatty}, \alpha_{Cirrhosis})$ where *p* denotes the pathology and the decision is made based on α_p. By experience if α_p is less than 0.5 for an unknown case, the confidence will be low.

The confidence of an unknown tested case characterized by its crisp data will be low (α_p<0.5) if its data is far from that data used to generate the rules. As long as the data of an unknown case is close to the data used for generation of any of the rules, the firing strength of the corresponding pathology, α_p will be greater than 0.5.

If the firing strength α_p is less than the selected threshold (0.5), the decision will not be made based only on the previously extracted rules, however after it is pathologically investigated, and correctly diagnosed , then the generated rule for this case is appended to the rule base.

RESULTS, DISCUSSION, AND CONCLUDING REMARKS

The system was developed using 140 cases, these cases were classified into two sets one to generate the rules while the other to test the system. In the first stage of developing this system, for any new case (defined by a crisp data and pathologically diagnosed), this data is used to

generate a new rule which appended to our data base rules. The number of the generated rules till now presented a good match between the decision from the system and the pathology examinations. The number of the rules is growing every day by appending a pathologically investigated and correctly diagnosed cases. Although the maximum number of the rules for (8) inputs and three fuzzy values is (3^8),the number of cases used to generate the rules till now presented a good performance, matched with the clinicians supports and examinations.

The results of this work revealed the potential value for considering the idea of fuzzy reasoning in tissue characterization of diffused liver 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 performance of the system is superior compared to the statistical methods and comparable to the last work of neural network
classification. This approach has proven very powerful role in the differentiation of early Cirrhosis from Normal. The proposed system can be readily used as a real time tool to recognize different subclasses of cirrhosis very efficiently.

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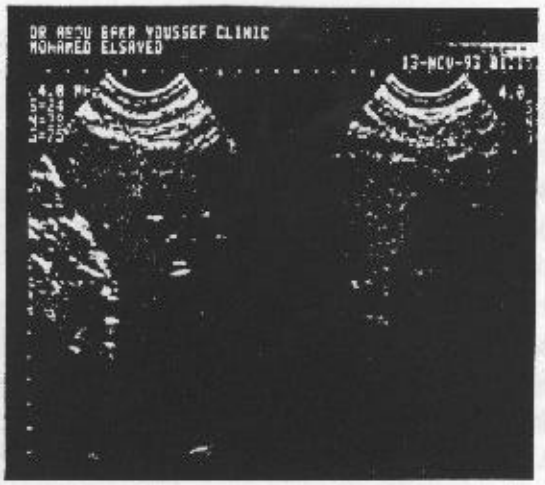

Figure 1(a) Normal B-mode ultrasound image

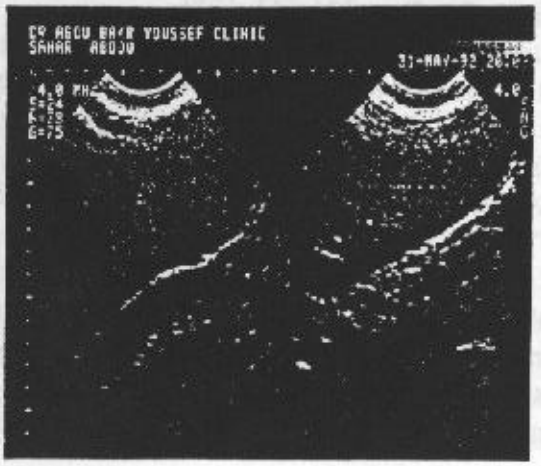

Figure 1(b) Fatty B-mode ultrasound image

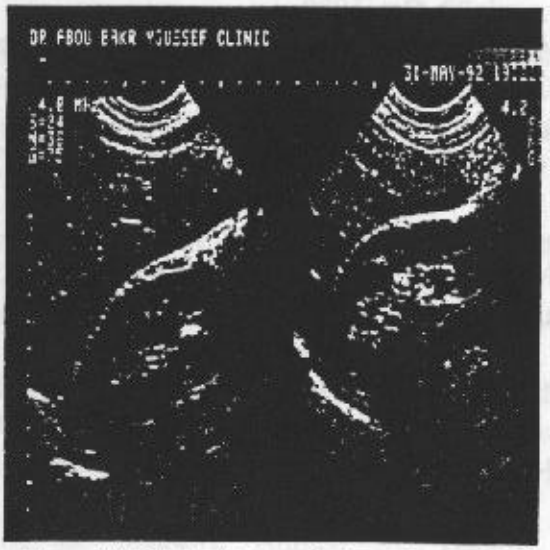

Figure 1(c) Cirrhotic B-mode ultrasound image

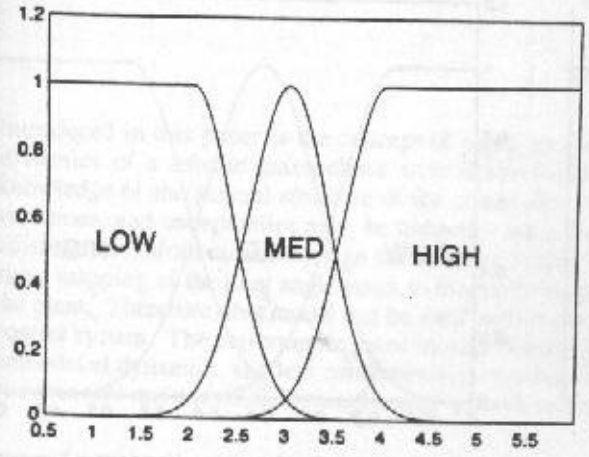

Figure 2(a) The Mean Grey Level Membership Functions

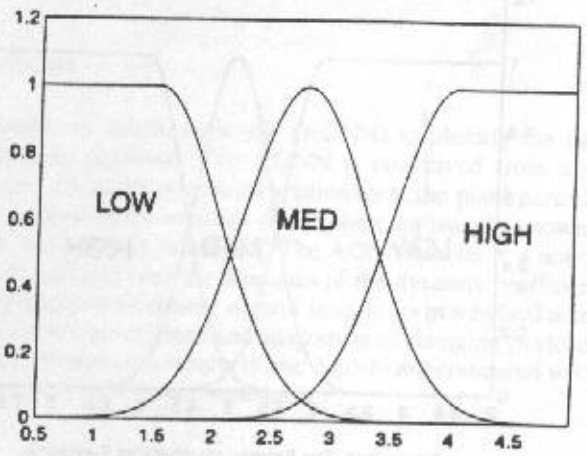

Figure 2(b) The Percentyle0.1 Membership Functions

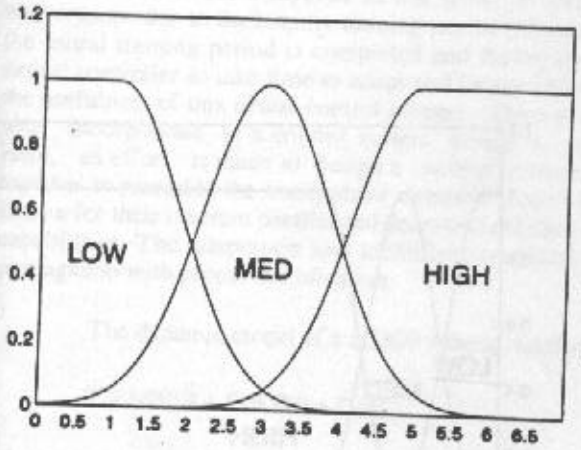

Figure 2(c) The Contrast Membership functions

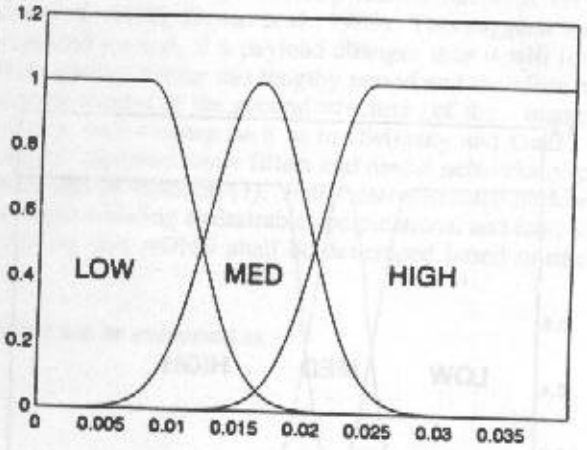

Figure 2(d) The Angular Second Moment Membership Functions

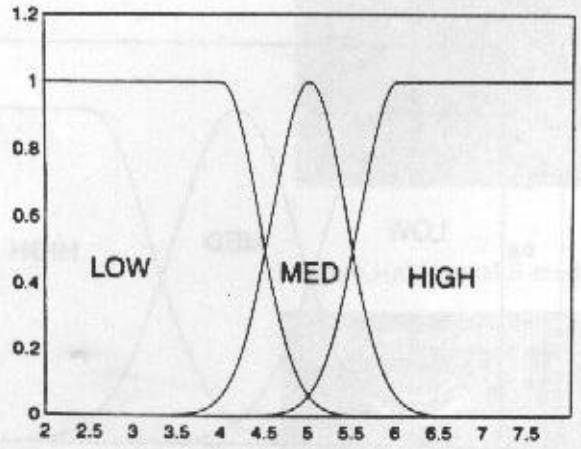

Figure 2(e) The Entropy Membership Functions

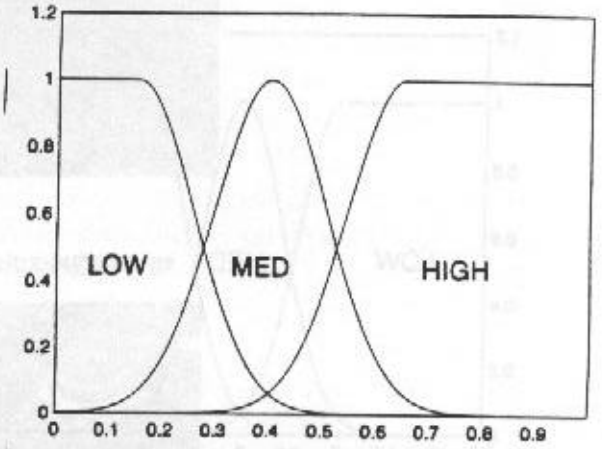

Figure 2(f) The Correlation Membership Functions

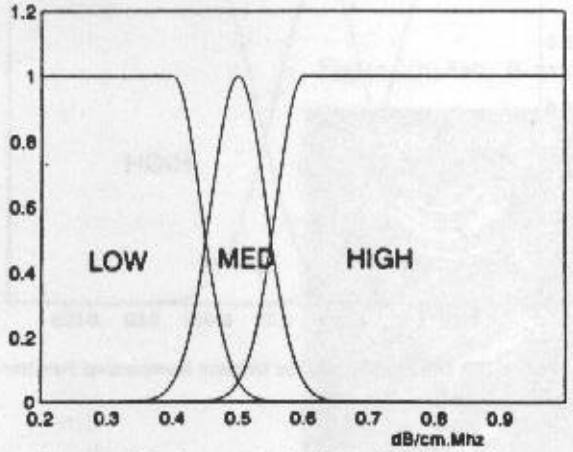

Figure 2(g) The Attenuation Coefficient Membership Functions

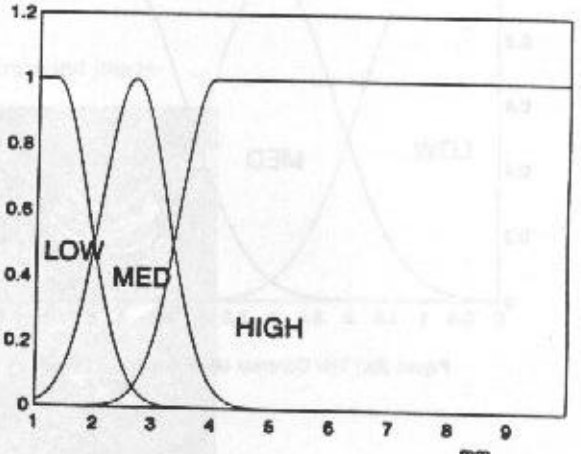

Figure 2(h) The Speckle Separation Membership Functions