An intelligent feature extractor for ultrasonic signals

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An intelligent feature extractor for ultrasonic signals

by

Ken E. Christensen

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Requirements for the Degree of
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1988
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1 INTRODUCTION

Feature extraction is the main objective of almost every signal analysis program. Many useful feature extraction methodologies and associated algorithms exist and almost all of them are very complex. In general, the algorithms used in signal processing systems are generally very difficult to alter after they have been coded. Only a few highly trained specialists with a deep understanding of the code are able make use of a signal processing algorithm in a manner other than its original purpose because the signal processing knowledge is completely embedded in the code of the algorithm. Commercial software packages which incorporate advanced technologies such as artificial intelligence exist [7,8], but these, too, tend to embed the signal processing knowledge within pattern recognition mechanisms. The recently developed "ICEPAK" system from Tektrend International Inc. is an example of a modern system which employs pattern recognition techniques to extract features from signals. To obtain accurate results, this type of pattern recognition system requires a large test bed of data for training purposes. A pattern recognition system such as this will produce good results only if trained well. After the system has been trained, the knowledge used to evaluate the signals is lost in the weighting factors of of the system [16]. When an error occurs in a system of this type, it is very difficult if not impossible to adjust the decision making process. Also, if a system such as this is to be used to analyze a different type of signal, the
There exists a need to extract the signal analysis knowledge from the control strategies of the signal processing algorithms. This would enable users of the feature extractor to understand exactly how the system reached a particular conclusion and would allow them to alter the knowledge to gain the best results. With this purpose in mind, the Feature Evaluation Process, FEAP, was designed to be used in the Flaw Classification Expert System, FLEX, being developed at the Center for Nondestructive Evaluation at Iowa State University. FEAP produces a set of feature-confidence pairs for a particular input signal. Using fuzzy sets, users of the system are allowed to alter the decision making process to meet their specifications. In this way, the knowledge of the expert is separated from the inference strategies of the feature extractor.

Research for this project has taken place over the last two years at the Center for NDE. To enable the people of the research team to view the signals, a visual interface was developed. This visual interface allows the user to display the time domain, frequency domain, integrated time domain and doubly integrated time domain responses of a particular signal. Decision trees were formed for each signal feature to model the decision-making process of a signal analysis expert. These decision trees were then used to create fuzzy decision trees where the propositions and conclusions are based on fuzzy set theory. Membership functions were constructed to model the fuzzy propositions and conclusions. This was aided by the development of a fuzzy set editor. Finally, the fuzzy decision trees were incorporated into FEAP to produce a set of confidence factors associated with the existence of each signal feature.
The general organization of this thesis is as follows. First, an overview of Nondestructive Evaluation and the Flaw Classification Expert System is given in Chapter 2. Chapter 3 presents a discussion of fuzzy set theory and its application to linguistic variables. Chapter 4 describes the development of the Feature Evaluation Process. Finally, the results of the research are discussed in Chapter 5.
2 BACKGROUND

2.1 Nondestructive Evaluation

The ability to evaluate the properties of mechanical structures and detect defects in these parts without destroying them is termed Nondestructive Evaluation (NDE) [6,5]. Using NDE methodologies, inspectors are able to analyze mechanical parts for possible failures before these failures cause any catastrophic loss. For example, critical parts in aircraft, nuclear reactors and highway bridges are analyzed using NDE techniques. Many methods of detection are employed by modern day inspectors. Among these methods, the most well known and widely used are simple visual inspection, radiography (X-rays), ultrasonic waves, eddy-currents, magnetic particles and penetrants.

The signals being evaluated by FLEX are specifically those produced in ultrasonic tests. A simple ultrasonic testing system is depicted in Figure 2.1. Here, an electronic pulser/receiver sends a sharp voltage pulse to an ultrasonic transducer. The transducer transforms the electric energy to mechanical energy by vibrating a piezoelectric crystal at high frequencies (typically $10^6$ to $20 \times 10^6$ cycles/second (Hz.)). This mechanical energy then travels through the host material to any flaws. Part of this energy is reflected off the flaw in the same manner sound echos off a wall. This reflected energy is then received by the same transducer in a pulse-echo
system as shown in Figure 2.1 or by another transducer in the case of a pitch-catch system. The reflected energy is transformed back to electrical energy by the receiving piezoelectric crystal and sent back to the receiver to be digitally stored or displayed [14]. The resulting voltage pulses are called the time domain response of the flaw. Fourier methods, such as the fast Fourier transform (FFT) can be used to produce an analogous frequency domain response. For example, the time and frequency response waveforms produced from an ultrasonic test of a 200 by 400 micron spheroidal void in titanium is shown in Figure 2.2.

When testing a particular flaw, it is advantageous to take ultrasonic measurements from more than one viewing angle, since multiple views will yield more information concerning the structure of the flaw. This additional information enables a more precise characterization of the defect. Although a typical commercial system might be limited to viewing defects from only two or three viewing angles, a research system recently developed at the Center for NDE at Iowa State University allows an inspector to examine flaws from many viewing angles within a hemisphere [17]. FLEX has been designed to use such additional information, when available, to make a more precise conclusion as to the classification of a flaw.

2.2 FLEX—An Expert System for Flaw Classification

The Flaw Classification Expert System (FLEX) developed at the Center for NDE at Iowa State University is designed to classify flaws as either crack-like or volumetric by analyzing the signals from ultrasonic tests taken from different viewing angles [15,13]. Flaw type determination is necessary in order to invoke the proper flaw characterization algorithms, Figure 2.3. FLEX, therefore, is a vital
Figure 2.1: Ultrasonic Testing System
Figure 2.2: Time and Frequency Response Signals of a 200 by 400 Micron Void
element in the development of a complete flaw characterization procedure.

FLEX is composed of two cooperating systems as illustrated in Figure 2.4. Before the signal data are analyzed, non-flaw dependencies are removed using the measurement model developed by R.B. Thompson and T.A. Gray at the Center for NDE [18]. The first intelligent system, the Feature Evaluation Process (FEAP), then analyzes this preprocessed data for a set of predefined features and assigns a confidence factor associated with the existence of each of these features. Confidence factors are numbers in the range $[-1, 1]$ where $-1$ indicates certain disbelief in the existence of a feature and $+1$ indicates certain belief in the existence of a feature. A set of nine partitions of the range $[-1, 1]$ was developed to map English terms to these confidence factors, Table 2.1. Such partitions allow for a more natural interface to the human user.

FEAP passes the results of its analysis, given in terms of confidence factors, to a second system, FLAP (an acronym for Flaw Evaluation Process). FLAP, which is structured as a rule-based expert system, then performs the actual flaw classification.

Figure 2.5 depicts the inference engine of FLAP. An explicit audit trail of the conclusions reached by FLAP and a graphical representation of the audit trail is made available to the user. Both FEAP and FLAP manipulate the confidence factors using methods developed by B.G. Buchanan and E.H. Shortliffe for the MYCIN project [2]. A complete description of FLAP can be found in the Master's thesis written by S.M. Nugen at Iowa State University [12]. The design and development of FEAP is discussed in Chapters 4 and 5 of this thesis.

The overall goal of the FLEX project was to demonstrate the feasibility of
Figure 2.3: Flaw Characterization Decision Tree
Figure 2.4: Block Diagram of FLEX
### Table 2.1: Confidence Factors

<table>
<thead>
<tr>
<th>Region</th>
<th>English Term</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.0</td>
<td>CF ≤ -0.8 Certain Disbelief</td>
</tr>
<tr>
<td>-0.8</td>
<td>CF ≤ -0.6 Strong Disbelief</td>
</tr>
<tr>
<td>-0.6</td>
<td>CF ≤ -0.4 Moderate Disbelief</td>
</tr>
<tr>
<td>-0.4</td>
<td>CF &lt; -0.2 Weak Disbelief</td>
</tr>
<tr>
<td>-0.2</td>
<td>CF ≤ +0.2 Uncertain</td>
</tr>
<tr>
<td>+0.2</td>
<td>CF &lt; +0.4 Weak Belief</td>
</tr>
<tr>
<td>+0.4</td>
<td>CF &lt; +0.6 Moderate Belief</td>
</tr>
<tr>
<td>+0.6</td>
<td>CF &lt; +0.8 Strong Belief</td>
</tr>
<tr>
<td>+0.8</td>
<td>CF ≤ +1.0 Certain Belief</td>
</tr>
</tbody>
</table>
Figure 2.5: FLAP Inference Engine
applying artificial intelligence techniques to the NDE problem domain. FLEX also provides a formal representation of the NDE knowledge of flaw classification. Industrial sponsors of the Center for Nondestructive Evaluation can use FLEX as a starting point in developing expert systems of their own.
3 FUZZY SET THEORY

An important issue in designing intelligent systems is the management of uncertainty [22]. Since the knowledge base of an intelligent system is a storage area for human knowledge, and since human knowledge is imprecise, it is usually the case that the knowledge base is a collection of rules which are not totally precise.

Much of human reasoning is approximate rather than precise in nature. For example, people reason in approximate terms when choosing which route to take to a desired destination or how much to bet in poker. It can be argued that only a small fraction of human thinking is precise. Similarly, unlike strict mathematical sets, real world sets are imprecise or fuzzy. For example, consider the set of all “expensive cars”. Clearly, Mercedes-Benz is a member of this set. Yugo is not a member of this set. But, it is not always easy to decide. Consider Honda in the context of “expensive cars”. Honda is only “partially” in this set since it is actually in the set “moderately expensive”. Fuzziness could be eliminated by giving the exact definition (dollar value) of “expensive”, but this would distort the meaning of the term as used by people in everyday life.

To make fuzzy concepts precise by choosing an arbitrary cutoff is contrary to common sense. As another example, consider the set of tall men. Using ordinary mathematical sets, a strict height cutoff is required. All men whose height is less than the cutoff are not included in the set and all men whose height is greater than
the cutoff are included in the set. This implies that it is possible for two men to
differ in height by only a fraction of an inch and one be considered tall and the
other not tall. To alleviate this disparity, gradations in membership are required.
Fuzzy sets contain these gradations. Fuzzy sets provide partial membership within
a set. In the next two sections, an overview of fuzzy sets and their relation to strict
mathematical sets is presented. The final section of this chapter describes how
linguistic variables can be characterized using fuzzy sets. This characterization of
linguistic variables is implemented in the Feature Evaluation Process of FLEX to
handle the lack of precision in the feature extraction heuristics. The use of fuzzy
sets as a framework for the management of uncertainty in intelligent systems makes
it possible to handle the lack of precision and vagueness of human knowledge in a
consistent, mathematical manner.

3.1 Strict Mathematical Sets

An strict mathematical set is a collection of objects from some universe of
discourse, \( U \). A set can be characterized by a function which maps an element of
\( U \) to 1 if the element is contained in the set and to 0 if the element is not contained
in the set. Given a subset, \( A \), of the universe, \( U \), the membership function of \( A \) is
defined [4] to be,

\[
\mu_A(x) = \begin{cases} 
1 & \text{if } x \in A \\
0 & \text{otherwise}
\end{cases}
\]

The set \( A \) can be written as,

\[
A = \int_{x \in U} \mu_A(x)/x
\]
where the integral sign denotes the continuous union of an infinite set of elements. In set notation, the / is a way of representing an ordered pair. The ordered pair 1/a indicates a is a member of the set and the ordered pair 0/b indicates b is not a member of the set. Using this notation, the finite set $A = \{a, b, c, d\}$ from the universe $\{a, b, c, d, e, f\}$ may be written as,

$$A = 1/a + 1/b + 1/c + 1/d + 0/e + 0/f$$

or more simply,

$$A = 1/a + 1/b + 1/c + 1/d$$

where the + symbol indicates union.

The union of two sets $A$ and $B$ is the set of all elements which are in either $A$ or $B$ and is represented by the equation,

$$A + B = \bigcup_{x \in U} \max(\mu_A(x), \mu_B(x))/x.$$

The intersection of two sets $A$ and $B$ is the set of all elements which are in both $A$ and $B$ and can be written as,

$$A \ast B = \bigcap_{x \in U} \min(\mu_A(x), \mu_B(x))/x.$$

The complement of $A$ is the set of all elements in the universe which are not in $A$ and is represented by the equation,

$$\overline{A} = \bigcup_{x \in U} (1 - \mu_A(x))/x.$$

The empty set, the set with no elements, can be written as,

$$\emptyset = \bigcup_{x \in U} 0/x.$$
A is a subset of $B$ iff every element of $A$ is also an element of $B$.

$$A \subseteq B \iff \forall (x \in U) \left[ \mu_A(x) \leq \mu_B(x) \right]$$

Two sets $A$ and $B$ are equal iff they contain exactly the same members.

$$A = B \iff \forall (x \in U) \left[ \mu_A(x) = \mu_B(x) \right]$$

### 3.2 Fuzzy Sets

Fuzzy Sets were introduced by L.A. Zadeh in 1965 \[19\]. In strict mathematical sets, an element is either included in a set or excluded from the set. Fuzzy sets map elements to one of an infinite number of degrees of membership. This is accomplished by extending the range of $\mu$ to the interval $[0, 1]$. As the $\mu$-value of an element approaches 1, the membership of the element within the set increases. An element with full membership in the set will have a $\mu$-value of 1. Total exclusion from the set is indicated by a $\mu$-value of 0. The definitions of sets previously described in this chapter remain valid. Thus, fuzzy sets are a generalization of ordinary mathematical sets.

An example of fuzzy sets is now given. Consider the following two fuzzy sets of the universe $U = \{0, 1, \ldots, 10\}$.

$$A = 1/0 + 1/1 + 1/2 + .5/3 + .2/4$$

$$B = .1/2 + .4/3 + 1/4 + 1/5$$

Using the definitions previously defined,

$$A + B = 1/0 + 1/1 + 1/2 + .5/3 + 1/4 + 1/5$$
\[ A \ast B = .1/2 + .4/3 + 1/4 + 1/5 \]
\[ \overline{A} = .5/3 + .8/4 + 1/5 + 1/6 + 1/7 + 1/8 + 1/9 + 1/10 \]

The following set, \( C \), is a subset of \( A \).
\[ C = .8/1 + .5/3 + .1/4 \]

The support of a fuzzy set \( A \) is the set of all elements of \( A \) with \( \mu \)-values greater than 0.
\[ \text{sup}(A) = \{ x | \mu_A(x) > 0 \} \]

The height of \( A \) is the largest \( \mu \)-value of any element in the support of \( A \).
\[ \text{hgt}(A) = \max(\mu_A(x)) \]

A fuzzy set is normal iff \( \text{hgt}(A) = 1 \). The following fuzzy set is not normal.
\[ A = .5/1 + .4/2 + .1/3 \]

This fuzzy set can be normalized by multiplying each element by the quantity \( 1/\text{hgt}(A) \) assuming \( \text{hgt}(A) > 0 \).
\[ \text{hgt}(A) = \max(0.5, 0.4, 0.1) \]
\[ = 0.5 \]
\[ \text{norm}(A) = 1/1 + .8/2 + .2/3 \]

In general, the intersection of two normal fuzzy sets in not normal. If this is not desired, the result may be normalized as above.
The definitions of union, intersection and complementation are used to apply fuzzy sets to Boolean expressions [4]. The properties of union, intersection and complementation of fuzzy sets are listed in Table 3.1.

It is important to note that no changes have been made to the definitions used in ordinary mathematical set theory. Ordinary set theory is a subset of fuzzy set theory. However, one important law of standard set theory which does not hold for fuzzy sets is the law of excluded middle. For a set $A$,

$$A \ast \overline{A} \neq \phi.$$ 

The following example shows this anomaly.

$$U = \{1, 2, 3, 4\}$$

$$A = 1/1 + .8/2 + .3/3$$

$$A^\prime = .2/2 + .7/3 + 1/4$$

$$A \ast A^\prime = .2/2 + .3/3$$

Intuitively, violation of the law of excluded middle makes more sense that it might at first seem. Consider the following statements.

- Those who understand fuzzy sets should explain them to others.

- Those who do not understand fuzzy sets should read some technical papers concerning fuzzy sets.

There is the possibility for the existence of an "in-between" person who should explain fuzzy sets to others and would gain knowledge by reading a few technical papers.
Table 3.1: Properties of Union, Intersection and Complementation

<table>
<thead>
<tr>
<th>Property</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commutativity</td>
<td>$A + B = B + A$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot B = B \cdot A$</td>
</tr>
<tr>
<td>Associativity</td>
<td>$A + (B + C) = (A + B) + C$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot (B \cdot C) = (A \cdot B) \cdot C$</td>
</tr>
<tr>
<td>Distributivity</td>
<td>$A + (B \cdot C) = (A + B) \cdot (A + C)$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot (B + C) = (A \cdot B) + (A \cdot C)$</td>
</tr>
<tr>
<td>Dominance</td>
<td>$A + U = U$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot \phi = \phi$</td>
</tr>
<tr>
<td>Identity</td>
<td>$A + \phi = A$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot U = A$</td>
</tr>
<tr>
<td>Absorption</td>
<td>$A + (A \cdot B) = A$</td>
</tr>
<tr>
<td></td>
<td>$A \cdot (A + B) = A$</td>
</tr>
<tr>
<td>De Morgan's Law</td>
<td>$(A + B) = \overline{A} + \overline{B}$</td>
</tr>
<tr>
<td></td>
<td>$(A \cdot B) = \overline{A} \cdot \overline{B}$</td>
</tr>
<tr>
<td>Involution</td>
<td>$\overline{(A)} = A$</td>
</tr>
</tbody>
</table>
3.3 Application of Fuzzy Sets to Linguistic Variables

One of the most significant applications of fuzzy sets is their implementations to characterize linguistic variables. Humans use words rather than numbers to characterize values of variables as well as the relations between them. For example, the size of a person may be described as very tall and the appearance of a person as very attractive. The use of these qualitative words in place of quantitative values leads to a lack of precision in the characterization of the variables [21].

Consider a variable which describes the size of a pulse in a signal. This variable will be called Pulse. Pulse will be assumed to take on the values in the interval [0,100]. Pulse can also take on values such as large and small. Words like large and small, which play a role analogous to physical units, are called primary terms [21]. These primary terms can be characterized by membership functions [20,11] defined over the universe of discourse, $U = [0,100]$. Let large be defined as follows.

$$
\text{large}(x) = \begin{cases} 
0 & \text{if } x < 20 \\
1 & \text{if } x > 80 \\
1 - ((80 - x)/60) & \text{otherwise}
\end{cases}
$$

It is also possible to calibrate the membership functions using secondary terms such as very and slightly. Most implementations of secondary terms consist of raising the membership function to some power. The greater the degree of membership, the greater the power.

$$
\text{large} = f(x) \\
\text{very large} = f(x)^2 \\
\text{slightly large} = f(x)^5
$$
3.4 Advantages and Drawbacks of Fuzzy Sets

Fuzzy sets allow imprecise linguistic terms to be represented and manipulated in a precise mathematical manner. Traditional set theory can thus be extended to manage the uncertainties introduced by imprecise knowledge.

One of the most serious drawbacks of fuzzy sets is that the membership functions are context-sensitive. Consider the linguistic variable large. One can see problems in using the same membership function for large mouse and large elephant. This problem can be alleviated by requiring the linguistic terms be specific.
In this example, *large-mouse* and *large-elephant* would have different membership functions associated with them.

In a comparison of paradigms for the management of uncertainty in intelligent computer systems written by N.S. Lee et al. [9], fuzzy set theory was characterized as having a moderately strong theoretic background and the theory was moderately complex. Fuzzy sets were also characterized as easy to implement.

An actual implementation of fuzzy linguistic variables in the Feature Evaluation Process will be discussed in the following chapter.
4 THE FEATURE EVALUATION PROCESS

The Feature Evaluation Process (FEAP) is one of two cooperating systems within the Flaw Expert (FLEX) being developed at the Center for Nondestructive Evaluation at Iowa State University. It is the job of FEAP to evaluate a set of preprocessed ultrasonic signals for a set of predefined features. The data are preprocessed to remove all of the non-flaw dependencies from the signal such as transducer type, material attenuation, receiver settings, etc. FEAP can then evaluate signal feature characteristics of flaw-type only. FEAP assigns a confidence factor (Table 2.1) as to the existence of each of the predefined features (Table 4.1) of the signals. These confidence factors are then processed by the expert system FLAP, which classifies the defect represented by the signals as either crack-like or volumetric, Figure 2.4.

FEAP uses basic signal processing algorithms to extract the features from the signals. Many of these algorithms contained hidden heuristics embedded deep in code. A major goal in the design of FEAP was to remove these heuristics from the algorithms and allow the user to alter these heuristics in a clean, precise manner. FEAP employs fuzzy sets to accomplish this task. The use of fuzzy sets to separate the signal processing knowledge from the inferencing strategies is detailed later in this chapter.

The FLEX system, including FEAP, is being developed on a Symbolics 3670
LISP workstation using Symbolics' extended Common LISP. This system employs a bit-mapped graphics display and a mouse. FLEX uses both of these features extensively in its user interface. The computer code, however, has been designed to allow it to be used on systems without these features. A computer system without these features will not be able to make use of some of the user-friendly tools developed for FLEX such as the Visual Interface System, the Fuzzy Set Editor and the Visual Explanation Facility.

4.1 The Visual Interface System

One of the first components of FLEX developed was the Visual Interface System. The need to visualize the signals was necessary for the domain experts at the Center for NDE to properly evaluate the signals. It later served as an interface between FEAP and the human operator both for input of data and confirmation of the correctness of calculated results. The Visual Interface System allows the user to load a particular data file or a set of data files into the FLEX system. The signal data files are stored separately on the hard disk of the Symbolics 3670. The data in these files can be either time or frequency domain response data from an ultrasonic test. A naming convention was adopted to name all frequency domain data files "sca*.xxx", where the "sca" is an abbreviation for scattering amplitude data. Time domain data are stored in files named "flaw*.xxx". The "*" and "xxx" represent the viewing angle reference number and the test set extension name respectively.

When a file is loaded into the system, the data in the file are manipulated to fill a data structure which contains all of the information known about the stored signal. This data structure contains the time domain, frequency domain, integrated
time domain and doubly integrated time domain data of the ultrasonic test along with the data set identification, frequency sampling increment and time sampling increment. This data structure also contains fields where additional information produced and used by FEAP is stored during the feature evaluation process.

After a file is loaded into the system, the user can display the time domain, frequency domain, integrated time domain and the doubly integrated time domain data on the screen in any of five windows. With five windows available, the user can display different data sets simultaneously for comparison purposes.

The Visual Interface System allowed FEAP to prompt the user for information it could not itself compute in the early stages of its development. As FEAP matured, all of the user prompts were eliminated. In the final version of FEAP, the Visual Interface System is only used to confirm the calculation of a single feature.

4.2 Derivation of the Features and Decision Trees

Members of the technical staff at the Center for NDE were consulted as to features they used to classify a flaw as either crack-like or volumetric. From these interviews, it was determined that the features used in the evaluation of the signals could be derived from a combination of fundamental theoretical and numerical knowledge of signal responses from known flaws and heuristic knowledge from actual experimentation. As an example, the Kirchhoff model of a crack-like flaw response [1] predicts a linearly increasing amplitude with increasing frequency in the frequency domain response if the transducer is at normal incidence to the crack [3], Figure 4.1a. More exact numerical models confirm the existence of this feature with some added modulation on the response. However, in actual experimentation,
this feature has been found to exist only to the center frequency of the transducer, Figure 4.1b. This type of heuristic knowledge is incorporated in the evaluation of this feature. A complete description of the derivation of all of the signal features being evaluated by FEAP will be available in the Fall of 1988 in a set of application notes to be distributed by the Center for NDE at Iowa State University.

The features currently used by FEAP in the signal evaluation process are found in both the frequency and time domain signals, Table 4.1. Using both the frequency and time domain features has proven to be very useful. For example, some signals from known volumetric flaws look very crack-like in one domain but in analyzing the other domain, an accurate determination of the flaw being volumetric is possible.

After establishing the features to be used in the system, a decision tree was developed for each feature. An example of the decision tree created for determining the existence of flash points in the time domain signal is shown in Figure 4.2. A decision tree gives a step by step procedure for evaluating the signal for a given feature. After traversing the decision tree to a leaf, an appropriate confidence in the existence of the feature in question is assigned to the signal. A discussion of confidence factors can be found in Chapter 2. The decision trees for evaluating the features were tested by manually evaluating actual sets of experimental data produced at the Center for NDE. These manual evaluations established the validity of the decision trees.
Figure 4.1: Derivation of Linear Increasing Amplitude
Table 4.1: Features Evaluated by FEAP

<table>
<thead>
<tr>
<th>Feature</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Leading Edge Pulse</td>
<td>Time</td>
</tr>
<tr>
<td>Flash Points</td>
<td>Time</td>
</tr>
<tr>
<td>Rayleigh Wave</td>
<td>Time</td>
</tr>
<tr>
<td>Ringing</td>
<td>Time</td>
</tr>
<tr>
<td>Linearly Increasing Amplitude</td>
<td>Frequency</td>
</tr>
<tr>
<td>Plateau With Shallow Nulls</td>
<td>Frequency</td>
</tr>
<tr>
<td>Decreasing Amplitude With Deep Nulls</td>
<td>Frequency</td>
</tr>
<tr>
<td>Sharp Nulls</td>
<td>Frequency</td>
</tr>
</tbody>
</table>
Figure 4.2: Original Flash Points Decision Tree
4.3 The Use of Fuzzy Sets for the Management of Uncertainty

A main objective of FEAP is to capture the NDE knowledge of signal feature evaluation. If traditional signal processing routines were used in FEAP, much of the feature evaluation knowledge would be embedded in the code and hidden from the human operator. This knowledge needed to be made explicit and easily modifiable.

Another problem arose while developing the decision trees used in the evaluation of the features. In traditional modeling of the decision-making process, strict cutoffs within the proposition are made. Consider the following statement: "If a small number of people are present, then use room A". How many is "a small number"? Traditional computer programs would define "a small number" to be, say five. This leads to problems when there exist a large number of cases where the value of the variable in question is very near the cutoff value. In the example above, say the alternative to using room A is room B which has the capacity for fifty people. If it was possible to squeeze seven people into room A and in most cases there were six or seven people attending, a strict cutoff of five would lead to wasted resources. This is exactly the problem found in the decision trees. In many of the propositions, there exist variables such as "small number of pulses" and "large amplitude". Assigning a strict cutoff to these decisions would cause some features to go undetected when in actuality, the features were present but did no quite meet the cutoff. Also, in assigning values to the cutoffs and coding these cutoffs into the algorithms, the knowledge of the feature evaluation would become very hard to modify. The knowledge would be lost in the code.

To manage the uncertainty in the decision trees and at the same time make the feature evaluation knowledge more explicit, fuzzy sets were employed. In assigning
a fuzzy set to each proposition in the decision trees, the propositions in the decision trees need not be totally true or totally false. Using fuzzy sets, a proposition can have a value in the range $[0,1]$ with 0 indicating no truth in the proposition and 1 indicating total truth in the proposition. The mapping of the linguistic variable of the proposition to fuzzy membership functions was performed much like the characterization of primary linguistic terms described in Chapter 3 [20,11].

A hypothetical example of a decision tree using fuzzy sets is shown in Figure 4.3. The value of truth of each proposition is in parentheses in each proposition, denoted by ovals in the decision tree. The conclusions, denoted by the boxes, are at the leaves of the decision tree. In each conclusion box is the Boolean expression defining the path to the conclusion box. When evaluating a decision tree, all of the propositions are invoked. After determining the fuzzy value of each proposition, the value of every conclusion is calculated using the union, intersection and complementation properties of fuzzy sets. For example, the Boolean expression for Conclusion 4 is $A \cdot \overline{B} \cdot C \cdot D$. The Boolean AND is equivalent to intersection. Complementation of a fuzzy value $X$ is simply $(1 - X)$. Using these properties, the fuzzy value of Conclusion 4 is

$$\min(0.8, (1-0.4), 0.7, 0.3) = 0.3.$$  

After every conclusion is assigned a fuzzy value, the conclusion with the maximum fuzzy value is chosen. Conclusion 5 is chosen in the example in Figure 4.3.

In addition to the having fuzzy sets assigned to each proposition in its decision tree, each feature was assigned a fuzzy membership function. This membership function will return a fuzzy value corresponding to a parameter relative to the
Figure 4.3: Hypothetical Example of a Fuzzy Decision Tree
feature. Figure 4.4 illustrates the membership function for Flash Points. The parameter mapped by the fuzzy set characterization is the ratio of the minimum flash point amplitude to the maximum flash point amplitude. In the decision trees formed for the evaluation of features, each conclusion was assigned a confidence factor. The confidence which FEAP assigns to the feature is the fuzzy value of the feature multiplied by the confidence associated with the conclusion chosen in traversing the decision tree. For example, if the fuzzy value of a function was 0.6 and the conclusion chosen in the traversal of the decision tree is assigned a Strong confidence, the confidence in the feature is $0.6 \times 0.7 = .42$ where 0.7 is the value of Strong.

As an example of an actual feature evaluation using fuzzy sets, consider the frequency response signal in Figure 4.5 and the decision tree for the feature Normal Incidence, Figure 4.17. The fuzzy sets assigned to the propositions of this decision tree are illustrated in Figures 4.6, 4.7 and 4.8. The fuzzy set for the feature Normal Incidence is shown in Figure 4.9.

Proposition 1 analyzes the location of $A_{\text{max}}$, the top of the first “hump” in the signal. In the case of the example signal, $A_{\text{max}}$ occurs at 6.8 MHz. Referring to the fuzzy set in Figure 4.6, it can be seen that a value of 1.0 is assigned to Proposition 1. Now turning to Figure 4.7, 6.8 MHz. causes the value 0.14 to be returned from the fuzzy characterization function for Proposition 2. Proposition 3 is assigned a value of 0.09 since only one relative minimum exists between the minimum frequency and the frequency at which $A_{\text{max}}$ occurs. After computing the values of the propositions, the values of the conclusions are calculated. The
Figure 4.4: Membership Function for Flash Points
Figure 4.5: Frequency Domain Response of an Ultrasonic Signal
Figure 4.6: Fuzzy Set for Normal Incidence Proposition 1
Figure 4.7: Fuzzy Set for Normal Incidence Proposition 2
Figure 4.8: Fuzzy Set for Normal Incidence Proposition 3
Figure 4.9: Fuzzy Set for Normal Incidence
results of these calculations are reported below.

\[
\text{Conclusion 1} = \min(1.0, 0.14) \\
= 0.14 \\
\text{Conclusion 2} = \min(1.0, (1 - 0.14)) \\
= 0.86 \\
\text{Conclusion 3} = \min((1.0 - 1.0), 0.09) \\
= 0.0 \\
\text{Conclusion 4} = \min((1.0 - 1.0), 0.91) \\
= 0.0
\]

Since the conclusion with the maximum value is \textit{Conclusion 2}, its confidence value is chosen. The confidence value of \textit{Conclusion 2}, "Moderate Belief" maps to 0.5 (Figure 2.1).

An estimate of the linearity of the signal response between the minimum frequency and the frequency at which \textit{Amax} occurs is recorded in a variable named "area\_ratio". The value of "area\_ratio" for this signal is 0.94 which causes the function characterizing the feature \textit{Normal Incidence} to return the value 0.76. This value is multiplied by the confidence in this value which was determined to be 0.5 by \textit{Conclusion 2}. The value reported in the output of FEAP for the confidence in \textit{Normal Incidence} for this signal is \((0.5 \times 0.76) = 0.38\).

The LISP implementation of the feature \textit{Normal Incidence} can be found in the Appendix.
The decisions trees for the features being evaluated by FEAP are depicted in Figures 4.12 through 4.20.

4.4 The Fuzzy Set Editor

To enhance the ease the altering the fuzzy sets used in FEAP, a Fuzzy Set Editor was developed. With the fuzzy set editor, the user is able to display, create, modify or delete a fuzzy set.

All of the fuzzy sets implemented in FEAP are formed from one general purpose function. The function used is called the S-function, Figure 4.10 [9].

\[
S(x; \alpha, \gamma) = \begin{cases} 
0 & \text{if } x \leq \alpha \\
2 \left(\frac{x - \alpha}{\gamma - \alpha}\right)^2 & \text{if } \alpha \leq x \leq \beta \\
1 - 2 \left(\frac{x - \gamma}{\gamma - \alpha}\right)^2 & \text{if } \beta \leq x \leq \gamma \\
1 & \text{if } x \geq \gamma
\end{cases}
\]

where \( \beta = \frac{\alpha + \gamma}{2} \)

Figure 4.10: The General Purpose S-function

The parameters required for the S-function are \( \alpha \) and \( \gamma \). A third term, \( n \), was added to further generalize the S-function. The function used to generate a particular membership function returns the value

\((S(x; \alpha, \gamma)^n)\).\)
Three addition parameters are also used by the fuzzy editor but are not required by FEAP. These parameters are the minimum and maximum value of \( z \) to be displayed and the label for the horizontal axis of the displayed fuzzy set. All of the parameters for each fuzzy set are stored in a list along with the name of the fuzzy set. All of the lists of parameters are stored in a file on the hard disk of the Symbolics 3670. When invoking FEAP, any file containing fuzzy set parameters may be specified. This enables comparisons to be made between the results of two feature extraction sessions using different fuzzy set parameters.

4.5 The Output of FEAP

There are two files produced by FEAP. The first file contains the confidence factors associated with the existence of the features for each signal evaluated by FEAP. This file then is the input file for FLAP. To insure compatibility between FEAP and FLAP, a BNF grammar [10] was developed for this interface, Figure 4.11. The name of this output file is specified to be

"FEAP_FEAT_EVAL.<test-set-id>".

The second file produced by FEAP is the FEAP audit trail. This file contains an explicit audit trail detailing the intermediate parameters used by FEAP, all of the fuzzy values of the propositions and conclusions of each decision tree and the confidences assigned to the existence of each feature. This audit trail serves two purposes. It can be used for locating errors in the decisions of FEAP when the conclusion differ from those expected and it can be used a record of the decision-making process for verification of the results in the future.
The results of FEAP will be stored in a list conforming to the following specifications:

\[
\begin{align*}
((\text{Signal-1 (Feature-1 CF)} \ldots (\text{Feature-n CF})) \\
(\text{Signal-2 (Feature-1 CF)} \ldots (\text{Feature-n CF})) \\
\vdots \\
(\text{Signal-m (Feature-1 CF)} \ldots (\text{Feature-n CF}))
\end{align*}
\]

where \( m = \# \text{ of viewing angles} \)
where \( n = \# \text{ of features} \)

where \( \forall \text{ Signal-i, Signal-j : Feature-k of Signal-i = Feature-k of Signal-j} \)
\[
1 \leq i \leq m, \quad 1 \leq j \leq m, \quad 1 \leq k \leq n
\]

where \( \text{Signal} \quad ::= \quad \langle \text{name}\rangle\langle\text{viewing angle}\rangle . \langle\text{test-id}\rangle \)
\( \langle\text{name}\rangle \quad ::= \quad \langle\text{char}\rangle\langle\text{char}\rangle\langle\text{char}\rangle \)
\( \langle\text{viewing angle}\rangle \quad ::= \quad \langle\text{digit}\rangle | \langle\text{digit}\rangle\langle\text{digit}\rangle \)
\( \langle\text{test-id}\rangle \quad ::= \quad \langle\text{digit-or-char}\rangle | \langle\text{digit-or-char}\rangle\langle\text{digit-or-char}\rangle \)
\( \langle\text{digit-or-char}\rangle \quad ::= \quad \langle\text{digit}\rangle | \langle\text{char}\rangle \)
\( \langle\text{char}\rangle \quad ::= \quad A|\ldots|Z|a|\ldots|z \)
\( \langle\text{digit}\rangle \quad ::= \quad 0|\ldots|9 \)

where \( \text{Feature} \quad ::= \quad \text{POS.PULSE} | \text{FLASH.POINTS} | \text{RINGING} \)
\( \quad | \text{CREEP.WV} | \text{RAYLEIGH.WV} \)
\( \quad | \text{NORMAL.INCI} | \text{DEEP.NULLS} \)
\( \quad | \text{SHALLOW.NULLS} | \text{SHARP.NULLS} \)

where \( \text{CF} \quad ::= \quad \langle\text{sign}\rangle\langle\text{zero-or-1}\rangle . \langle\text{digit}\rangle\langle\text{digit}\rangle \)
\( \langle\text{sign}\rangle \quad ::= \quad +|\ldots|\epsilon \)
\( \langle\text{zero-or-1}\rangle \quad ::= \quad 0|1 \)

Example:

\[
(\langle\text{"SCAI.t44" (RINGING 0.52) (SHARP.NULLS 0.69) . . . } \rangle . . . )
\]

This list is stored in a file named \text{FEAP.FEAT.EVAL.<test-id>}. 

Example:

\text{"FEAP.FEAT.EVAL.t44"}

Figure 4.11: Output of FEAP
Figure 4.12: Positive LEP Decision Tree
Figure 4.13: Flash Points Decision Tree
Figure 4.14: Rayleigh Wave Decision Tree
Figure 4.15: Creep Wave Decision Tree
Figure 4.16: Ringing Decision Tree
Figure 4.17: Normal Incidence Decision Tree
Figure 4.18: Shallow Nulls Decision Tree
Figure 4.19: Deep Nulls Decision Tree
Frequency Domain Signal

Sharp Nulls exist
*Sharp Nulls Proposition 1*

Yes

- \text{Sharp Nulls CF} = 0.8
  (Strong Belief)
  *Sharp Nulls Conclusion 1*

No

- \text{Sharp Nulls CF} = -0.8
  (Strong Disbelief)
  *Sharp Nulls Conclusion 2*

*Figure 4.20: Sharp Nulls Decision Tree*
5 SUMMARY AND DISCUSSION

The Feature Evaluation Process (FEAP) was developed to capture the NDE knowledge of signal analysis experts in an explicit, easily modifiable form. This was accomplished through the employment of fuzzy sets. The use of fuzzy sets allows the human operator to visualize exactly how the decisions in the feature extraction process are made and also makes a very user-friendly interface between the operator and the signal analysis algorithms. The convenience of the interface encourages the user to adjust the decision making process to suit his particular specifications. Fuzzy sets also allows the user to think in common English terms rather than hard coded numbers.

Another advantage of using fuzzy sets is that fuzzy sets smooth harsh cutoffs in the decision making process. This smoothing has led to more accurate results in the feature analysis. The reason for an increased performance of FEAP after implementing fuzzy sets is illustrated in the following example.

Before introducing fuzzy sets to FEAP, the second proposition in the decision tree for Normal Incidence read, “Is the frequency at which Amax occurs greater than \[\frac{1}{2} \times (f_{\text{max}} - f_{\text{min}}) + f_{\text{min}}\]?”. This proposition is based on the following heuristic used by the signal analysis experts. If Amax occurs in the last half of the frequency spectrum, there is a strong confidence in the existence of Linear Increasing Amplitude. Because the variables \(f_{\text{max}}\) and \(f_{\text{min}}\) are virtually constant in
most of the signals evaluated by FEAP, the value of the deciding frequency was also constant. The actual value for the cutoff frequency was 8.0 MHz. Before the employment of fuzzy sets, this decision was characterized by the set shown in Figure 5.1. In this figure, a value of 1.0 is interpreted as totally certain in the proposition being true and a value of 0.0 indicates total certainty in the proposition being false. It is important to note that the decision is either totally true to totally false.

It was discovered that in many the signals being evaluated, the frequency at which $A_{\text{max}}$ occurred was just under the 8.0 MHz. cutoff. Because of this, many of the signals were given a lower confidence in Normal Incidence than they actually should have been assigned.

Without changing the heuristic on which the proposition was based, the introduction of fuzzy sets caused these borderline signals to be evaluated more accurately. As can be seen in Figure 5.2, signals where $A_{\text{max}}$ occurs between 6 MHz. and 9 MHz. are assigned partial membership in the fuzzy set characterizing Normal Incidence Proposition 2. Assigning partial membership to this proposition caused a stronger conclusion to be reached. This also resulted in a stronger confidence in the existence of the feature Normal Incidence in the borderline signals. This stronger conclusion was more consistent with the intent of the original signal analysis heuristic. Thus, fuzzy sets captured this intent automatically without resorting to modifying threshold values as would be required in tradition decision-making methods employing strict cutoffs.

The major shortcoming of fuzzy sets, the need for the membership functions to be unambiguous, was overcome by using explicit variable names such as "many-large-extrema-exist-in-the-late-time-domain". This caused every variable to be
Figure 5.1: *Proposition 2* Decision Before Fuzzy Sets
Figure 5.2: *Proposition 2* Decision After Fuzzy Sets
characterized by a unique membership function. While this lead to many different membership functions and less generality in the membership functions, the use of explicit variable names guarantees unambiguous characterization of the variables. The Fuzzy Set Editor developed in parallel with FEAP made management of the fuzzy sets very painless.

In creating the decision trees for the analysis of the features, the heuristic knowledge of the NDE experts was formally recorded. A major mission of the Center for NDE, where the research for FEAP took place, is the transfer of NDE technology to the industrial sponsors of the Center. The Flaw Expert, FLEX, follows this mission by explicitly identifying and recording the heuristic knowledge used in the evaluation signals. FLEX will be made available to the industrial sponsors so that they can use it as a starting point in developing their own expert systems. Along with the heuristic knowledge of FLEX, the implementation of fuzzy sets in FEAP and a rule-based expert system, FLAP, will also be delivered.

FEAP is complete in its present stage of development. As with any computer program, enhancements will always be able to be added. The extension of fuzzy sets to the signal analysis functions used to calculate the propositions is a possible addition to FEAP. FEAP could also be extended to evaluate new features for ultrasonic signals and features of other types of NDE signals such as eddy current responses.
6 BIBLIOGRAPHY


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This appendix contains the LISP source code written to evaluate the feature *Normal Incidence*. A general idea of the implementation of fuzzy sets in FEAP can be obtained by reviewing this code.

The Flaw Expert, FLEX, including FEAP, FLAP and related tools, was encoded on a Symbolics 3670 LISP workstation using Symbolics’ Common LISP. Persons interested in a complete source code listing of FEAP should write a letter of request to the author at the Center for Nondestructive Evaluation, Ames Laboratory, Ames, IA 50011.
(defun lin-inc-ampl (lookangle)
  ;; 1. lookangle is a structure of type viewangle. defined in "file_loader.lisp"
  ;; 2. This function will evaluate the frequency domain signal of lookangle and
  ;; determine the confidence factor for NORMAL_INCI (a confidence in the
  ;; existence of linearly increasing amplitude with increasing frequency).

  (let ((Amax_MHz) ; Position of Amax in MHz.
        (fuzzy_Amax_not_near_fmin) ; Fuzzy value for Proposition 1
        (fuzzy_Amax_greater_than_half) ; Fuzzy value for Proposition 2
        (fuzzy_extrema_exist) ; Fuzzy value for Conclusion 1
        (conclusion1) ; Fuzzy value for Conclusion 1
        (conclusion2) ; Fuzzy value for Conclusion 2
        (conclusion3) ; Fuzzy value for Conclusion 3
        (conclusion4) ; Fuzzy value for Conclusion 4
        (area_list) ; List of areas to computer area ratio
        (area_ratio) ; Estimate of linearity
        (multiplying_factor) ; Confidence of the Strongest Conclusion
          
          ;; Find Amax -- The function find-Amax will return the point number in the data array
          ;; at which Amax occurs. This point number will be converted to a frequency in MHz and
          ;; stored in the variable Amax_MHz.

          (find-Amax lookangle)
          (setq Amax_MHz (* (viewangle-frequencty lookangle) (viewangle-Amax_index lookangle)))

          (format feap_audit_trail "-% Amax is at point -a = ~2.1$ MHz" ; viewangle-Amax_index lookangle) Amax_MHz)

          ;; Calculate the value of Proposition 1
          (setq fuzzy_Amax_not_near_fmin (Amax-not-near-min-freq Amax_MHz))
          (format feap_audit_trail "-% Normal Incidence Proposition 1 = ~2.1$ " ; fuzzy_Amax_not_near_fmin)

          ;; Calculate the value of Proposition 2
          (setq fuzzy_Amax_greater_than_half (Amax-greater-than-half Amax_MHz))
          (format feap_audit_trail "-% Normal Incidence Proposition 2 = ~2.1$ " ; fuzzy_Amax_greater_than_half)

          ;; Calculate the value of Proposition 3
          (setq fuzzy_extrema_exist (extrema-exit-between-points
                                       ; (viewangle-min lookangle) (viewangle-frequencty lookangle))
                            ; (viewangle-Amax_index lookangle)
                            ; (viewangle-frequency_relative_extrema lookangle)))
          (format feap_audit_trail "-% Normal Incidence Proposition 3 = ~2.1$ " ; fuzzy_extrema_exist)
Determine the fuzzy values of all the Conclusions using the fuzzy union property

(setq conclusion1 (min fuzzy_Amax_not_near_fmin
fuzzy_Amax_greater_than_half))

(setq conclusion2 (min fuzzy_Amax_not_near_fmin
(fuzzy-not fuzzy_Amax_greater_than_half)))

(setq conclusion3 (min (fuzzy-not fuzzy_Amax_not_near_fmin)
  fuzzy_extrema_exist))

(setq conclusion4 (min (fuzzy-not fuzzy_Amax_not_near_fmin)
 (fuzzy-not fuzzy_extrema_exist)))

(format feap_audit_trail "-% Normal Incidence Conclusion 1 = -2,1$" conclusion1)
(format feap_audit_trail "-% Normal Incidence Conclusion 2 = -2,1$" conclusion2)
(format feap_audit_trail "-% Normal Incidence Conclusion 3 = -2,1$" conclusion3)
(format feap_audit_trail "-% Normal Incidence Conclusion 4 = -2,1$" conclusion4)

;; Set the variable "multipliying factor" to the confidence in the
;; strongest Conclusion
(setq multiplying_factor
  (cond
    ((eq conclusion1 (max conclusion1 conclusion2 conclusion3 conclusion4)) 0.9)
    ((eq conclusion2 (max conclusion1 conclusion2 conclusion3 conclusion4)) 0.6)
    ((eq conclusion3 (max conclusion1 conclusion2 conclusion3 conclusion4)) -0.5)
    ((eq conclusion4 (max conclusion1 conclusion2 conclusion3 conclusion4)) 0.0)
  ))

(format feap_audit_trail "-% Normal Incidence Conclusion Confidence Factor = -2,1$"
  multiplying_factor)

(setq area_list (find-low-frequency-areas lookangle))
(setq area_ratio (/ (caddr area_list) (car area_list)))
(format feap_audit_trail "-% NORMAL_INCI confidence = -2,1$ -%"
  (fuzzy-lin-inc-amp multiplying_factor area_ratio))

;; Return the confidence in the feature NORMAL_INCI based on the confidence of the
;; strongest conclusion and the estimate of linearity, "area_ratio"
(list 'NORMAL_INCI
  (fuzzy-lin-inc-amp multiplying_factor area_ratio))
)

(defun fuzzy-lin-inc-amp (multiplying_factor area_ratio)

;; This function will return the confidence factor of the feature NORMAL_INCI
(let ((alpha) (gamma) (n) ; parameters of the fuzzy characterization function
  (parameter_list)
  )

;; Get the parameters for the characterizing function from the list of parameters
(setq parameter_list
  (retrieve-fuzzy-set-parameters "normal incidence" fuzzy_set_parameters))

(setq alpha (nth 1 parameter_list))
(setq gamma (nth 2 parameter_list))
(setq n (nth 3 parameter_list))

;; Calculate the value of the confidence factor
(* (s-function area_ratio alpha gamma n) multiplying_factor)
)
(defun extrema-exist-between-points (start_index end_index extrema_list)
  ;; This function will return the fuzzy value for Proposition 3
  (let ((alpha) (gamma) (n))
    (parameter_list)
    (setq parameter_list
      (retrieve-fuzzy-set-parameters
        "normal incidence proposition 3"
        fuzzy_set_parameters))
    (setq alpha (nth 1 parameter_list))
    (setq gamma (nth 2 parameter_list))
    (setq n (nth 3 parameter_list))
    ;; Determine fuzzy value based on the number of extrema
    (S-function (count-number-of-extrema start_index end_index extrema_list) alpha gamma n)
  )
)

(defun extrema-exist-between-points (start_index end_index extrema_list)
  ;; This function will return the fuzzy value for Proposition 3
  (let ((alpha) (gamma) (n))
    (parameter_list)
    (setq parameter_list
      (retrieve-fuzzy-set-parameters
        "normal incidence proposition 3"
        fuzzy_set_parameters))
    (setq alpha (nth 1 parameter_list))
    (setq gamma (nth 2 parameter_list))
    (setq n (nth 3 parameter_list))
    ;; Determine fuzzy value based on the number of extrema
    (S-function (count-number-of-extrema start_index end_index extrema_list) alpha gamma n)
  )
)

(defun count-number-of-extrema (start_index end_index extrema_list)
  ;; This function will count the number of extrema between two points
  (cond ((null extrema_list) 0.0)
    (T (+ (count-number-of-extrema start_index end_index (cdr extrema_list))
      (cond ((And (<= start_index (car extrema_list))
                 (<= (car extrema_list) end_index)) 1.0)
        (T 0.0)))))
)
(defun Amax-not-near-min-freq (Amax_MHz)
  ;; This function will return the fuzzy value for Proposition 1
  (let ((alpha) (gamma) (n)) ; parameters of the fuzzy characterization function
    (parameter_list)
      )
      
    (setq parameter_list
      (retrieve-fuzzy-set-parameters
        "normal incidence proposition 1"
        fuzzy_set_parameters))
    
    (setq alpha (nth 1 parameter_list))
    (setq gamma (nth 2 parameter_list))
    (setq n (nth 3 parameter_list))
    
    (setq parameter_list
      (retrieve-fuzzy-set-parameters
        "normal incidence proposition 1"
        fuzzy_set_parameters))
    
    (setq alpha (nth 1 parameter_list))
    (setq gamma (nth 2 parameter_list))
    (setq n (nth 3 parameter_list))
    
    ;; Determine fuzzy value based on the location of Amax
    (S-function Amax_MHz alpha gamma n)
      )
    
  (defun Amax-greater-than-half (Amax_MHz)
  ;; This function will return the fuzzy value for Proposition 2
  (let ((alpha) (gamma) (n)) ; parameters of the fuzzy characterization function
    (parameter_list)
      )
      
    (setq parameter_list
      (retrieve-fuzzy-set-parameters
        "normal incidence proposition 2"
        fuzzy_set_parameters))
    
    (setq alpha (nth 1 parameter_list))
    (setq gamma (nth 2 parameter_list))
    (setq n (nth 3 parameter_list))
    
    ;; Determine fuzzy value based on the location of Amax
    (S-function Amax_MHz alpha gamma n)
      )
    )