Fuzzy Syntactic Pattern Recognition Approach for Extracting and Classifying Flaw Patterns from an Eddy-Current Signal Waveform

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Abstract

In this paper, a general fuzzy syntactic method for recognition of flaw patterns and for the measurement of flaw characteristic parameters from a non-destructive inspection signal, called eddy-current, is presented. Solutions are given to the subtasks of primitive pattern selection, signal to symbol transformation, pattern grammar formulation, and event-synchronous flaw pattern extraction based on the grammars. Fuzzy attribute grammars are used as the model for the pattern grammar because of their descriptive power in the face of uncertain constraints caused by noise or distortion in the signal waveform, due to their ability to handle syntactic as well as semantic information. This approach has been implemented and the performance of the resultant system has been evaluated using a library of flaw patterns obtained from steam generator tubes in nuclear power plants by an eddy current-based non-destructive inspection method.

I. Introduction

The signal pattern recognition problems in material health monitoring applications, called Non-Destructive Evaluation (NDE) [1, 2], are very complicated tasks compared to general object pattern recognition problems. The pattern recognizer should extract interesting signal patterns caused by shape distortion from the continuously displayed signal waveform, and should then evaluate whether the distortion is caused by defect factors[1]. Recently, demand for increased material performance has led to more stringent requirements for detailed information about the detected harmful flaws in several NDE applications[1-3]. Merely finding the precise flaw location is not sufficient in many situations; defect size, shape, orientation, source and impact of the flaw on material properties should be determined so that reliability and productivity of the inspection process can be enhanced.

To solve these problems in NDE applications, much work on developing an automated defect signal identification and evaluation system has been reported[1-7]. However, much of the initial effort was purely numerical, using statistical pattern recognition techniques such as cluster analysis and template matching. Results of these early attempts were generally disappointing, mainly because of their failure to exploit such domain-specific characteristics as the structural knowledge induced from the physical structure of the tested material or to adopt appropriate mechanisms for handling the uncertainties resulting from the nature of the signal waveforms.

Eddy Current Testing (ECT)[2] is an important NDE technique with the characteristics mentioned above. ECT is widely used to detect anomalies in tubes used in nuclear power plants (NPP). Conventionally, ECT is done by human inspectors who must scrutinize a time-varying continuous signal waveform displayed on a screen to detect flaw signal patterns and classify them. Because of the high cost of manual inspection and the varying capabilities of the inspectors, some attempts to automate ECT signal inspections have been made[3-8].

In this paper, we propose a generalized fuzzy symbolic model to represent the ECT signal and a corresponding fuzzy syntactic pattern analysis framework to make problem-solving in this area an easier task. Many syntactic pattern recognition approaches to waveform analysis in one dimension already been applied to electro-cardiogram, well-log and seismic applications[10, 11]. However, because of the need to extend the analysis noisy and distorted shape, the proposed architecture exploits a new fuzzy syntactic pattern recognition framework by modifying and enhancing the traditional syntactic pattern recognition approaches.

A brief description of ECT for inspecting the health of steam-generator tubes in NPP is presented in the following section, and the overall architecture of the proposed system is described in section III. Detailed design and implementation of the proposed

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architecture is presented in the subsections following. Performance analysis of a prototype implementation is considered in section Ⅳ. Finally, section Ⅴ contains concluding remarks and suggestions for further research.

Ⅱ. Brief Description of the Application

ECT[1, 2] is a material health monitoring technique using eddy currents as the signal. The technique is especially effective for rapid detection of cracks, seams, and other flaws in thin-walled objects, and for sorting different materials in a given batch. These features make inspection of tubes in a nuclear power plant an excellent application of eddy current inspection. To detect tube anomalies, which might allow leakage of radioactive coolant, in a nuclear steam generator (SG), thousands of tubes are inspected by certified human inspectors during the annual inspection period of a nuclear power plant[2]. An eddy current probe scanned over the surface of a tube under test reacts to local variations caused by flaws, sludge, and roughness of the surface. Responses to different material flaws appear in the form of so-called eddy current Lissajous patterns in the impedance plane. The Lissajous pattern displays different two-dimensional contours according to the condition of the surface of the tube. Its trajectory and shape are related to the flaw type, and its lobe amplitude has a correlation with the flaw size.

Figure 1(a) shows the partial shape (a 'U' type) of a steam generator tube, Figure 1(b) displays horizontal and vertical strip signals, and Figure 1(c) shows various two-dimensional Lissajous patterns formed by the two strip signals against the locations on the tube. As shown in Figure 1(a), there are many plates, bars and sheets on the outside of the tubes such as the support plate (SP), anti-vibration-bar (AVB), upper tube sheet (UTS) and bottom tube sheet (BTS), which give some interference effects to the raw signal.

When the probe is passed through these regions, the interference effects show up as unusual Lissajous patterns, as shown in Figure 1(c). Moreover, the regions which are affected by the interference objects are also subject to other signal distortion effects, such as defects, sludge, dents, noise and probe wobbling. These regions are also prone to harmful flaws such as stress corrosion cracking, pitting, wear-scar and denting in the SG tubes[1, 2].

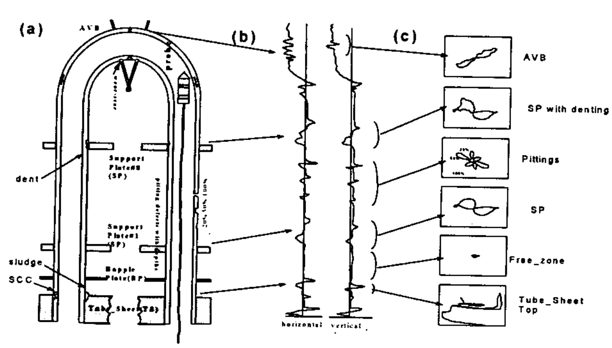


Fig. 1. ECT-based steam-generator tube inspection in NPP : (a) a shape of a SG tube and indicated locations; (b) two strip signals acquired from the tube; (c) temporal event pattern displayed on a two-dimensional Lissajous screen.

Ⅲ. Design of the Proposed Architecture

1. Overview

Figure 2 illustrates the design concepts and the proposed system architecture, which consists of a recognition part and a learning part. Since the recognition part is directly connected to a real-time eddy current signal acquisition device, it executes a series of subtasks to extract and analyze any flaw signal patterns as a flaw event.

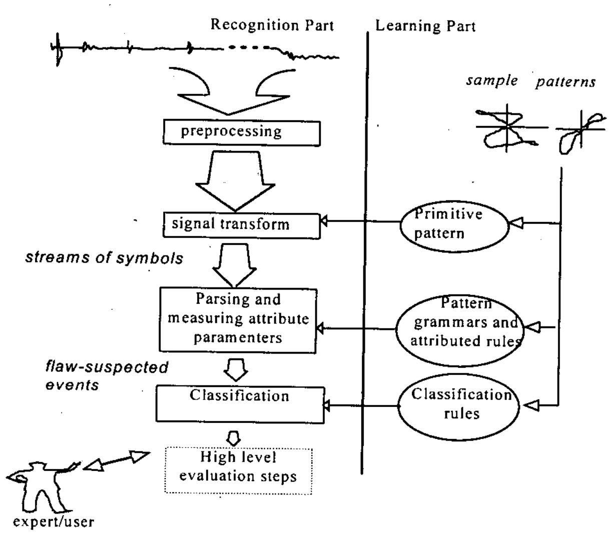


Fig. 2. Functional block diagram of the proposed system.

The learning part utilizes several knowledge bases that contain key information to extract and analyze flaw patterns obtained in the recognition component. Elements in the learning part are denoted by circles in Figure 2. The reasoning part is denoted by a box. It processes input data using the knowledge prepared by the learning part.

The first task is the preprocessing step for raw signals. This employs signal processing techniques such as least square approximation and median filtering to filter out noise factors in raw signals (detailed discussion of these techniques is not given here). The signal transformation function block in the recognition part transforms the raw eddy current Lissajous signals into a stream of pattern primitives. These are defined in the fuzzy primitive definition block in the learning part. The syntactic parsing block monitors and extracts pattern events which may be flaws, using a fuzzy syntactic grammar, which is defined in the syntactic grammar function block. The classification block firstly classifies extracted events into predefined classes and secondly reclassifies them according to whether they are harmful defect events or not, using attribute parameters that are measured synchronously in the parsing stage. The majority of extracted events are filtered out in this stage and only events that are definitely flaw suspects are sent to higher level evaluation steps. Because these high level evaluation steps are strongly domain dependent, we do not discuss them in this paper.

The proposed architecture can successfully perform input data filtering as noted by the thick gray arrows in Figure 2. Because of the filtering concept, the proposed system can detect and evaluate flaw signal patterns from a continuously produced input signal waveform in real time. Also, the separation of the two parts simplifies complex problems in the signal inspection process, and simplifies system maintenance. The following subsections explain the details of the design concepts.

2. Primitive Pattern Definition and Transformation

This section describes the transformation of the signal to a symbol stream. Because the shape, trajectory and amplitude of the eddy current Lissajous signals are the main clues [2] for detecting material flaw characteristics, the monitored signal is modeled as concatenations of amplitude and shape of signal segments. For the purpose of the transformation, we have defined a set of transformation functions that are borrowed from conventional two-dimensional shape analysis methods [9]. However, because of the uncertainty characteristics of eddy current Lissajous signals, we have designed a new signal representation model based on fuzzy set theory [14-17].

Since the signals are represented by a sequence of symbols, a signal model should define a set of symbol alphabets to represent the application signal. Our signal representation model has nine symbolic alphabets and each alphabet has fuzzy membership values for the fuzzy property. To generate the fuzzy symbolic alphabets, we have defined nine fuzzy membership functions: eight functions inherited from Freeman's eight directional chain symbols [9] to represent the shape information as shown in Figure 3(b), and one function to fuzzify the signal amplitude information as shown in Figure 3(c).

In order to reflect the shape and amplitude of a signal segment in the digitized raw signal as shown in Figure 3(a), two parameters, $\triangle h$, and $\triangle v$ are extracted to calculate θ and used to generate the fuzzy symbol alphabet.

Because the eight fuzzy symbols in Figure 3(b) represent the shape of the signals, the membership functions are defined using $\tan(\theta)$ as the gradient of the signal segment (see Figure (3a)). Therefore, the membership function $\mu_R(\tan(\theta))$ for any signal segment having a positive value in the interval [0, 1] indicates whether the segment is a member of the direction symbol $\Psi = \{b, c, d, e, f, g, h, i\}$. Similarly, the grade of membership expressing whether a line segment lies in the direction a may be

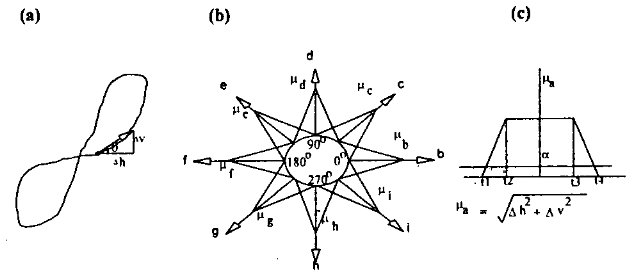


Fig. 3. Signal representation model: (a) transformation parameters for a signal segment in a sample Lissajous pattern; (b) eight fuzzy membership functions to represent the shape of a signal segment; (c) a fuzzy membership function to represent the amplitude of a signal segment.

expressed by the function shown in the Figure 3(c). This membership function is evaluated using $\triangle h$ and $\triangle v$ values. The threshold levels for the signal amplitude (a, t1, t2, t3, and t4 in Figure 3(c)) are constants defined when the fuzzy function is tuned by calibration of the signal acquisition condition. The membership values for the symbol a are used as a quantitative measure of the amplitude to solve thresholding problems for the signals as well as the degree of membership for the direction symbol. Because two fuzzy functions in Figure 3(b) overlap everywhere in a two-dimensional plane, the signals (S) are transformed into the stream of fuzzy symbols with their membership values k:

$$S = \sum_{i=1}^{n} P^{k}(i),\ \mathrm{n} = \text{number of signal segments}$$

where the P and k are evaluated according the following rules:

case $\mu_a(i) \geq \alpha$:

$$P(i) = \{r \mid \max(\mu_r(i)), r \in \Psi\},\ k = \mu_r(i) * \mu_a(i)$$

case $\mu_a(i) < \alpha$:

$$P(i) = \text{'a'},\ k = (1 - \mu a(i))$$

where i is the entry number in a signal segment, $\Psi = \{b, c, d, e, f, g, h, i\}$. Using the above rules, the raw signals such as those shown in Figure 4(a) are transformed into a stream of fuzzy symbols and their membership values as shown in Figure 4(b).

3. Pattern Grammar Definition and Parsing

Based on the stream of symbols described in the previous section, a grammar can now be defined for constructing the different pattern classes found in the real input signals. In syntactic pattern recognition, the task of recognition essentially amounts to parsing a linguistic representation of the patterns to be recognized, using a parser based on a so-called "pattern grammar" [9]. We have formulated a pattern grammar based on fuzzy attribute grammars [14-16] for description of the Lissajous shapes of the

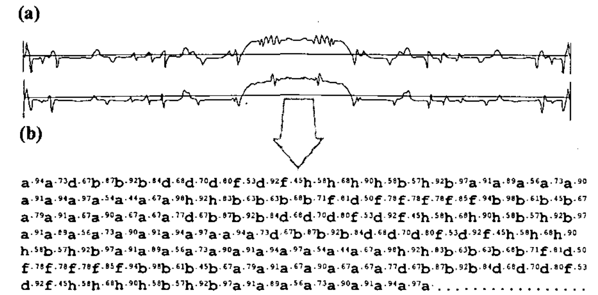


Fig. 4. Example of signal to symbol string transformation: (a) raw signal; (b) transformed fuzzy symbolic string.

eddy current signals, using a priori knowledge of the tested material structure. The grammar knowledge base must include the characteristics of all the sample pattern classes to be recognized. As shown in Figure 1, the shapes of the event signals in our application (nuclear SG tube) are categorized into many classes: BTS (bottom tube sheet), UTS (upper tube sheet), SP (support plate), AVB (anti-vibration bar), etc. For simplicity, this paper discusses only the AVB class event. A semantic rule associated with a syntactic rule is used for computing the value of the hypothesis expressed by the member of the syntactic rule on the left-hand side as a function of the membership functions of the components on the right-hand side. A set of fuzzy rules should be inferred for defining a class of sample patterns; for example, the grammar rules for the AVB and SP class of the event in Figure 3(a) are defined as follows:

Definition 1:

The fuzzy attribute grammar, for capturing and classifying the AVB event signals, is a 4-tuple

$G = (V_N, V_T, S, P)$

where

V_T = {a, b, c, d, e, f, g, h, i}, set of terminals such that $V_N \cap V_T = \varnothing$

V_N = {EVENT, AVB, D, H}, set of nonterminals, i.e., labels of a certain fuzzy set on, called fuzzy syntactic categories, with synthesized attribute sets followed by ';',

S = {AVB}, starting symbol ,

P, set of production rules as follows:

$EVENT \xrightarrow{1.0} AVB$ -- (p1)

; $\mu(AVB)$, $len(AVB)$, $peak-peak(AVB)$

$AVB \xrightarrow{1.0} D, H, D$ -- (p2)

; $len(D)$, $len(H)$, ..

$D \xrightarrow{1.0} d, D|d$ -- (p3, p4)

$D \xrightarrow{0.5} c, D|e, D|c|d$ ------------------------------ (p5, p6, p7, p8)

$D \xrightarrow{0.25} b, D|f, D|b|f$ ------------------------- (p9, p10, p11, p12)

$H \xrightarrow{1.0} h, H|h$ -- (p13, p14)

$H \xrightarrow{0.5} g, H|i, H|g|i$ -------------------------- (p15, p16, p17, p18)

$H \xrightarrow{0.25} f, H|b, H|f|b$ ------------------------ (p19, p20, p21, p22)

In the definition, the syntactic production rule " " means that B allows us to generate the hypothesis that there is a pattern *A* with plausibility of r. Each syntactic rule has associated semantic rules followed by ';' and the semantic rules as shown in p2 have two types. One is the derivation equation to calculate the possibility values. The semantic rules associated with the syntactic definition of D can be derived as follows.

In the case of (p4, p7, p8, p11, p12):

$$\mu_D = \{(1.0 \wedge \mu_d) \vee (0.5 \wedge (\mu_c \vee \mu_e)) \vee (0.25 \wedge (\mu_b \vee \mu_f)))\}$$

In the case of (p3, p5, p6, p9, p10):

$$\mu_D = \{ (1.0 \wedge (\mu_d \vee \mu_D)) \vee (0.5 \wedge (\mu_c \vee \mu_e \vee \mu_D) \vee (0.25 \wedge (\mu_b \vee \mu_f \vee \mu_D)\}$$

Therefore, each start symbol such as AVB in Definition 1 evaluates its semantic meanings as follows:

$$\mu_{AVB} = \{ \mu_{D1} \wedge \mu_H \wedge \mu_{D2}\}$$

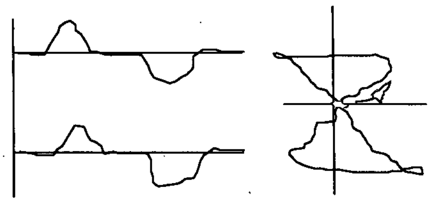
The other type of semantic rule, such as peak-peak (*AVB*) in p1 rule, is the definition of structural parameters: these should be measurements that characterize the event. A detailed description of this issue is presented in section III. 5.

Figure 5 shows another grammar definition that describes SP class objects and their actual shape in the Lissajous plane.

Thus, while parsing input streams, the predefined grammar rules such as Definition 1 are selectively fired according to a precondition which is the expected information for the domain model, such as the structure of the tested material, and a post condition which is the look ahead symptom input. Using this parsing method, the parser can effectively skip many of the signals acquired in the regions in a tube, which is of no interest. In this way, the performance of the proposed system can be greatly enhanced.

The results of the derivation are parse trees for each input string as shown on the right-hand side of Figure 6. The parsing system can capture any event patterns belonging to predefined sample patterns regardless of whether these have defect characteristics. It measures only the ratio of signal distortion by manipulating the semantic constraint derivation mechanism. Parse trees in Figure 6 show that the parser can capture not only normal signals but also abnormal ones using the same grammar. Finally, the m values of AVB at the roots of the parse trees notify the certainty values of the instance to the AVB class, and these values can be used as a measure of distortion ratio for the class instances. Therefore, using these values we can determine whether any event needs further evaluation. For example, if the m value of

(a) Sample Pattern(SP class)



(b) Grammatical Representation

P:

EVENT $\xrightarrow{1.0}$ SP

SP $\xrightarrow{1.0}$ FC,MS,LC
;μ_{shape}(FC),ln(FC)
;μ_{shape}(LC),ln(LC)
;ln(MS)

FC $\xrightarrow{1.0}$ C,F,I
;μ_{shape}(C),ln(C)
;μ_{shape}(F),ln(F)
;μ_{shape}(I),ln(I)

LC $\xrightarrow{1.0}$ I,F,C
;μ_{shape}(C),ln(C)
;μ_{shape}(F),ln(F)
;μ_{shape}(I),ln(I)

MS $\xrightarrow{1.0}$ a | a,MS

C $\xrightarrow{1.0}$ c,C| c
C $\xrightarrow{0.5}$ b| b,C|d |d,C
C $\xrightarrow{0.25}$ i|i,C|e|e,C
F $\xrightarrow{1.0}$ f,F| f
F $\xrightarrow{0.5}$ e| e,F|g |g,F
F $\xrightarrow{0.25}$ d|d,F|h|h,F
I $\xrightarrow{1.0}$ i,I| i
I $\xrightarrow{0.5}$ b| b,I|h |h,I
I $\xrightarrow{0.25}$ g|g,I|c|c,I

Fig. 5. (a) shape of signal pattern in SP class; (b) grammar definition for the SP class.

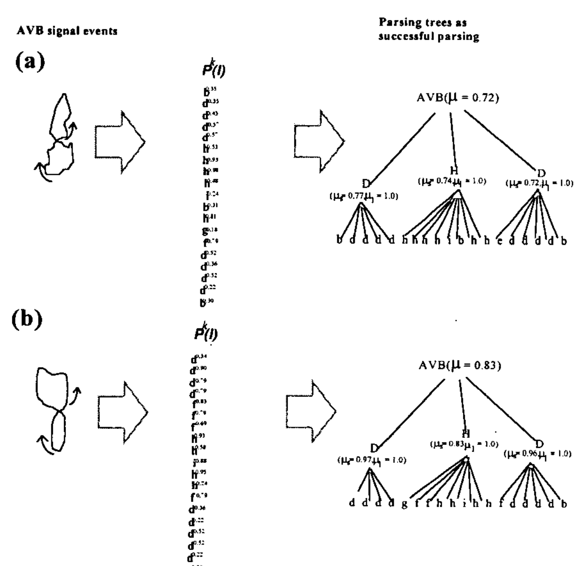


Fig. 6. Parsing examples for: (a) a normal AVB signal; (b) an AVB signal with defect.

an AVB instance is 0.99, it means that the shape and amplitude of the instance include only a little distortion, therefore, additional evaluation is unnecessary. The system performance can easily be increased because most of the extracted events are filtered out in this stage.

4. Parsing Algorithm

The structure of the hierarchical parsing procedure is depicted in Figure 7. At each stage context-free grammars such as those in Definition 1 or Figure 4(b) have been used. Let x denote the fuzzy symbol string for input signals.

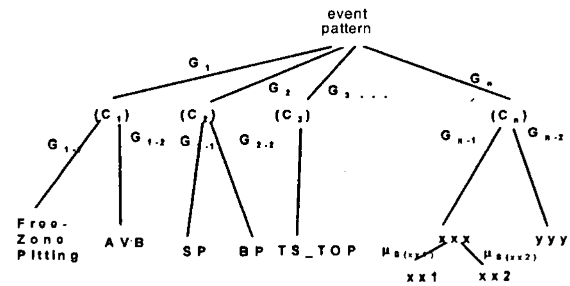


Fig. 7. The hierarchical parsing scheme.

Algorithm:

Stage 1: (primary classification): We define five classes Ci, $i = 1,2,\ldots,n$ as C_1 = {AVB, FreeZone_Pitting}, C_2 = {SP, BP}, C_3 = {TS_TOP), C_4 = {TS_END}, C_5 = {FreeZone_Dent}, ..., C_n = {,,,}.

Let Gi denote the grammar corresponding to class Ci and L(Gi) the language generated by Gi.

If x is found to be the empty string( ), halt parsing.

If not, and if x is parsed by the first stage grammar, then

$$x \in {}_C L(G_k),\ \text{if}\ \mu_{L(G_k)(x)} = \max_{1 \le i \le n} \mu_{L(G_i)}(x),\ k = 1,2,\ldots,n$$

If $x \in {}_C L(G_i)^6$ and i = class group has only one class then stop; otherwise go to the second stage.

Stage 2: We come here if there are contradictory decisions in the first stage $x \in {}_C L(G_i)$ or $x \in {}_C L(G_j)$. We now bring sub-grammar G_{ij} into the string then :

$$x \in {}_C L(G_{jk}),\ \text{if}\ \mu_{L(G_{jk})(x)} = \max_{1 \le i \le n} \mu_{L(G_{ji})}(x),\ k=1,2,\ldots,n \text{ and } j$$

denote the class which has several subclasses

If $x \in {}_C L(G_i)$, where x belongs to a subclass k in j parent class; then stop, otherwise go to the third stage.

Stage 3: Some G_{jk} define a number of semantic attributes as shown in Definition 1 or Figure 3(b). The values of the semantic attribute used as the three stage classification rules as followed:

$$\mu_{L(G_{jk})}(x) = \max[\ \mu_{L(G_{jk})}(x),\ \mu_{L(G_{ji})}(x)],\ i.e.\ x \in {}_C L(G_{jk})$$

In this stage, the classification is not, strictly speaking, syntactic in nature but the syntactic parser helps to get the values of the semantic attributes using the proper grammar firing sequence.

5. Parameter Measurement and Classification

By the guidance of the syntactic parsing scheme mentioned in previous sections, the structural parameters in event patterns can be measured in real time. Figure 8 shows the event attribute parameters that are extracted from the parsing stage and that are used as the decision criteria to classify the features of the flaws.

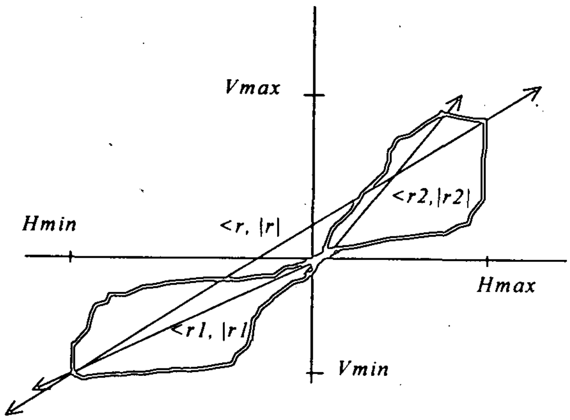


Fig. 8. The meaning of event attributes parameters.

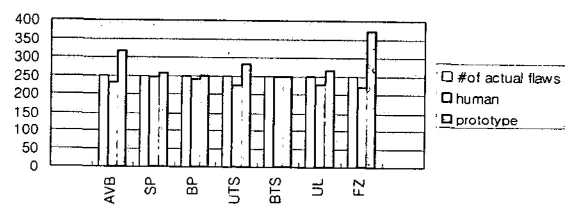
For example, shape description parameters such as Vmax, Vmin, Hmax, Hmin, and trajectories of subevents are used to classify the flaw types, and amplitude parameters such as < r, |r|, < r1, < r2 are used to evaluate the depth of flaws in the tested materials. There are many other considerations not described in Figure 8, such as material property, location of the flaw and previous inspection data, which are taken into account in deciding whether an event is a harmful flaw. These are not part of the scope of this paper but should be included in higher level evaluations such as a knowledge base evaluation step using an expert system and/or a neural network [3].

IV. Implementation and Experimental Results

We had previously developed a flaw pattern recognition system implemented using a crisp syntactic pattern recognition approach [5]. However, this system extracted too excessive events to reduce the task of human inspectors and was vulnerable to noisy input data. To solve the problems in the old system, a new prototype has been developed based on the fuzzy syntactic pattern recognition concepts proposed in this paper. The new prototype was fully implemented in C/C++ under Windows95. The prototype can process ECT signals of any SG tube very quickly, requiring 2 sec/channel, compared with about 1 min/channel for a human inspector. This performance makes it possible to implement the proposed concepts in a PC-based automatic ECT signal inspection system in a real-time environment. We have experimented with this system using hundreds of field data sets collected during inspections by a qualified human inspector. In each experiment, for each pattern class, 1000 patterns were prepared as test samples from field data. The test samples consisted of 250 samples with harmful flaws, 250 samples with harmless flaw signal patterns and 500 trivial samples that had no relation to the tested class. To verify the experimental results, several human inspectors with a certification of LEVEL II class expert [2] participated in the experiments. Table 1 illustrates the average results of the experiments.

As shown in Table 1, the prototype system caught all indicated events although it overestimated in some cases. On the other hand, the human inspectors frequently missed events, particularly small-scale ones. For relatively large-scale and simple shape events such as BP or SP, the evaluation results between two decision makers were comparable. Because UTS signal patterns produce complex Lissajous contours due to the composition of several distortion factors, the results of the proposed system were slightly worse for that class than the human inspectors. However, the overextraction ratio of suspected flaw events was reduced to below 30% compared with over 70% on average with the old system [5]. The remaining overestimation can be reduced by adding a dedicated domain-specific knowledge-based classifier for each signal pattern.

Table 1. Experimental results for harmful flaws in indicated regions.



AVB (anti-vibration bar), SP (support-plate), BP (baffle plate), UTS (upper tube sheet), BTS (bottom tube sheet), UL (u-band limit), FZ (free-zone defects)

In spite of the problem of overestimation, the experiment has demonstrated that the proposed system can be used in field situations as an automated flaw extraction and evaluation tool and can enhance the productivity and reliability of human inspectors. Because such systems are critical for safety in nuclear power plants, the reliable detection of flaw signal patterns is the most important criterion, rather than performance factors such as overestimation ratio or speed.

V. Conclusion

The proposed architecture incorporates the two main characteristics of the behavior of human inspectors. The first of these is the use of shape and trajectory of the signal pattern as the main clues in detecting flaw symptoms, and the other is that human inspectors only pay attention to designated signal portions in the huge amount of contiguously displayed signal data.

The fuzzy symbolic representation of signal data could successfully represent the shape and trajectory properties of ECT signals in spite of including noise and shape distortion problems. The proposed data-driven parser was designed to reproduce the second characteristic of the human inspectors behavior by implementing an elimination scheme for those signal portions that do not indicate events. This scheme allows the performance of the proposed system to be maximized.

The flaw detection capability of the prototype achieves better results than those of even experienced inspectors because the prototype never misses any flaw signal patterns even when the scale of the flaw is small, whereas human inspectors show varying capabilities for such patterns. However, the analytic capability of the prototype is not superior to human capability because the current prototype produces about 20~30% of overestimated event patterns that are not indicated by human inspectors. The overestimation ratio will be reduced drastically by extending the prototype to a multi-channel parsing architecture, and by adopting further domain-specific knowledge processing concepts such as expert system or neural network approaches at the high level evaluation stages.

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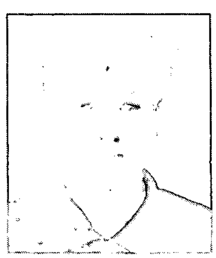

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