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Application of Fuzzy Reasoning for Filtering and Enhancement of Ultrasonic Images

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Abstract **- This paper presents a new type of an adaptive fuzzy operator for detection of isolated abnormalities, and enhancement of raw ultrasonic images. Fuzzy sets used in decision rules are defined for each image based on empirical statistics of the color intensities. Examples of the method are also presented in the paper.**

I. Introduction

Ultrasonic testing is one of the techniques used for nondestructive characterization of materials. In this work our interest is in one of its variations called contact scanning, where one front surface and two back surface ultrasonic pulses obtained using the pulse-echo configuration are digitized and stored at every scan location. These digitized pulses are used to compute ultrasonic properties versus frequency like phase velocity, cross-correlation velocity (not a function of frequency), reflection coefficient, attenuation coefficient and others [2-4]. Ultrasonic properties can be used to form ultrasonic images where values of a given property (at any frequency within transducer bandwidth) are represented by corresponding gray or color scale values. On a raw ultrasonic image each point (pixel) represents a single location for which ultrasonic data were collected. An example of a raw ultrasonic image representing a phase velocity[1] at 60 MHz is shown in Figure 1. Ultrasonic images from contact scans are typically enhanced using linear or cubic interpolation. Enhanced images are used to determine areas which correspond to undesired properties of a tested material. Figure 2 represents an enhanced ultrasonic

[1] Explanation of *phase velocity* is given in the Appendix.

image obtained directly from the raw image shown in Figure 1. Note three red and two blue "circles" in the image (dark circles on black and white illustrations). Each of these circles corresponds to a single point on the raw ultrasonic image; they are examples of "undesired phenomena" for further image analysis. In general, while constructing an ultrasonic image we are interested in global trends, thus properties of separated points are irrelevant. These "undesired" isolated points on the raw ultrasonic image should be identified and filtered before the image is enhanced. Figure 3 shows an enhanced image created from a filtered ultrasonic image of Figure 1.

Existence of the undesired points on the ultrasonic images can be attributed to:

1. Corruption of the ultrasonic pulse data. It usually occurs during digitization of analog data and has random nature. There are several types of these pulse data abnormalities, and only few of them can be detected by a direct analysis of digital pulses.
2. Ultrasonic pulse data is collected and digitized correctly, but properties of the tested material at these isolated points are "significantly" different from its neighbors.
3. Intrinsic uncertainties in data used for calculation of ultrasonic properties, like total difference in phase between first and second back reflection, used to calculate phase velocity.

The aim of this paper is to construct adaptive fuzzy operators for automatic detection of isolated suspicious points on an ultrasonic image. These points once detected can be either removed to facilitate creation of smoother enhanced image, or further investigated to determine the nature of their origin.

A method of fuzzy operator synthesis, presented in this paper, employs usage of statistical data obtained from a raw ultrasonic image, like histograms of pixel intensity or histograms of intensity differences between neighboring pixels. The data are processed and used to generate fuzzy sets representing desired versus undesired image contents.

II. Structure of the Fuzzy Operator

Let us start with a description of a fuzzy operator for image processing similar to the one presented in [1].

A. Generalized description of fuzzy variables

Each pixel of an image is processed by fuzzy rules applied to a set of pixels belonging to a rectangular window (neighborhood) centered on that pixel. As the window scans each pixel of the image, one at a time, a new pixel of the resulting image is generated by means of fuzzy reasoning. Fuzzy variables can be defined by using any function (or relationship) of interest for the processing and can be expressed as followings:

$$
\begin{aligned}
v_1 &= f_1(p_1, p_2, \ldots, p_m) \\
v_2 &= f_2(p_1, p_2, \ldots, p_m) \\
&\ldots \\
v_n &= f_n(p_1, p_2, \ldots, p_m) \\
o &= f(p_c, p'_c)
\end{aligned} \qquad \textbf{(1)}
$$

where v_1, v_2, ..., v_n are the input variables, o is the output variable, p_1, p_2, ..., p_m are luminance (intensity) values of the pixels in the window, p_c and p'_c indicate luminance of the pixel in the center of the window before and after processing, respectively.

B. Fuzzy Rulebase

The reasoning structure uses two types of rules: *THEN-rules* and *ELSE-rules*. Each THEN-rule includes n antecedents linked by fuzzy "AND" logical operators and only one consequent. The antecedents are related to input variables and the consequent to the output variable. The overall rulebase is composed of many THEN-rules and only one (global) ELSE-rule. The following rulebase contains r THEN-rules:

$$
\begin{array}{ll}
\text{IF } (v_1 \text{ is } A_{11}) \text{ AND } \ldots \text{ AND } (v_n \text{ is } A_{n1}) & \text{THEN } (o \text{ is } B_1) \\
\text{IF } (v_1 \text{ is } A_{12}) \text{ AND } \ldots \text{ AND } (v_n \text{ is } A_{n2}) & \text{THEN } (o \text{ is } B_2) \\
\ldots & \\
\text{IF } (v_1 \text{ is } A_{1r}) \text{ AND } \ldots \text{ AND } (v_n \text{ is } A_{nr}) & \text{THEN } (o \text{ is } B_r) \\
 & \text{ELSE } (o \text{ is } C_0)
\end{array} \qquad (2)
$$

where A_{ij} is a fuzzy set associated with variable v_i in the j-th rule, B_j is the consequent set of the same rule and C_0 is the consequent of the ELSE-rule. The ELSE-rule assures that the inference is successfully executed even if no THEN-rules are fired.

III. Synthesis of the Fuzzy Operator

A. Approach

In the approach presented here we attempt to follow a human way of deciding which points on an a raw ultrasonic image might be considered "suspicious". A typical decision is simple:

A point is suspicious if its intensity is significantly different from the intensity of the surrounding points.

We shall try to implement this "simple" decision in a fuzzy rulebase. The main difficulty is establishing what "significantly different" constitutes. The difficulty stems from the fact that human decisions are more qualitative than quantitative, and are not easily translated into numerical values.

We shall approach this problem by investigating statistical properties of image intensities. Figure 4 shows a histogram of pixel intensities of the raw ultrasonic image of Figure 1. Figure 5 presents histogram of an absolute value of intensity difference between neighboring points. Underlying distributions, represented by these histograms, can be used to represent "suspicious" points. We can mark a point as suspicious if its intensity value is in a tail of the image intensity value histogram, and its minimum difference of intensity to neighboring points is in a tail of the image intensity difference histogram. Since distribution types (image intensity, intensity differences) are unknown and are dependent on an image content, standard methods of statistical analysis are not well applicable here. Thus, we shall investigate possibility of using these histograms to generate fuzzy sets representing points with "atypical" intensity values and fuzzy sets representing points in which intensities are "quite" different than their neighborhood.

B. Creation of fuzzy sets

Let us introduce a normalization operator, N:

$$N[f(x)] = \frac{f(x) - \min f(x)}{\max f(x) - \min f(x)} \tag{3}$$

After normalization, function $f(x)$ takes on values from the interval [0,1]. Let s denote pixel intensity value, and d denote a minimum difference between the given point intensity and intensities of its neighboring points.

The fuzzy set, A_d, representing *high-intensity-difference* is created by taking the negation of the normalized inverted sum of an intensity value histogram, $h_d(d)$:

$$A_d(d) = 1 - N[\int_d^{\infty} h_d(x)\,dx] \tag{4}$$

Plot of the membership values of the fuzzy set A_d versus intensity difference d is shown in Figure 6.

The fuzzy set A_s representing *atypical-intensity* is obtained by taking a minimum of the negated cumulative sum, and the negated inverted cumulative sum, of the image intensity value histogram, $h_s(s)$.

$$H_s^{+}(s) = \int_{-\infty}^{s} h_s(x)\,dx \tag{5}$$

$$H_s^-(s) = \int_s^{\infty} h_s(x)\, dx \tag{6}$$

$$A_s(s) = \min\{1-N[H_s^-(s)],\ 1-N[H_s^+(s)]\} \tag{7}$$

Plot of membership values of the fuzzy set A_s versus intensity value s is shown in Figure 7.

Using definitions of the above defined fuzzy sets we construct the following decision rule: The output of evaluating a rule is a certainty value[2], in the 0 to 1 range, representing degree to

IF (point's intensity **is** a *very atypical-intensity*)
AND
(minimum difference of point's intensity **is** a *very high-intensity-difference)* **(8)**

THEN this point **is** *suspicious*

which a point is "suspicious". For the purpose of filtering we can set some certainty level, so when it is met we can mark the point as the one to be filtered out.

IV. Examples

The algorithm was tested on phase velocity images for four circular ceramic samples, named SN2, SN3, SN4 and SN6 [5]. The first sample, SN2, was used for calibration, the other samples were used for testing. Figures 8 to 11 shows examples of modification of fuzzy sets by hedge operators. Two standard hedge operators, *very* and *extremely*, were tested. They are implemented by rising membership values of a fuzzy set to the power of 3 and 5 respectively. First two columns of Table 1 compare number of points selected as "undesired" (suspicious) using different certainty levels shown in first column, and *high* and *extremely* hedges shown in second and third column. In general, *extremely* is less permissive than *very* in selecting points, qualitatively however the points selected are usually the same. Samples SN3, SN4 and SN4 were evaluated using the hedge *very*.

[2] Certainty value should not be mistaken with probability.

	Points selected				
Certainty value	$SN2_{very}$	$SN2_{extremely}$	SN3	SN4	SN6
0.99	1	1	1	1	1
0.95	5	4	5	8	7
0.9	8	6	7	10	9
0.85	11	8	16	19	12
0.8	14	9	19	30	17
0.75	17	11	24	33	22

Table 1: Number of points selected for different samples.

Figures 12 through 17 represent graphically how different confidence levels, using sample SN2, affect the quality of the filtered and then enhanced image. Based on these results level of confidence 0.9 was chosen. Figures 18 through 23 show comparison between raw enhanced images and images which were first filtered using our algorithm and then enhanced. The confidence level used for all of them was 0.9. Note changes in color scale: for filtered images the ranges are smaller. It is a highly desirable effect since it helps to better visualize microstructural gradients.

V. CONCLUSIONS

In this paper an adaptive fuzzy image processing operator was presented. The operator was primary developed for processing of raw ultrasonic images, however it can be easily applied in other image processing areas. The adaptiveness of the operator steams from the way the fuzzy sets used in the operator's fuzzy rulebase are generated. The sets are generated for each processed image individually using statistical data about image pixel intensities and intensities differences.

The introduced, relatively simple adaptive fuzzy operator is quite robust in finding suspicious points in raw ultrasonic images. In the presented fuzzy operator detects only isolated points, it would be desirable, however, to make it sensitive not only to isolated points but also to small areas. Other fuzzy rules can be added to the operator rulebase, for instance to improve treatment of border points.

In presented examples the adaptive fuzzy operator was used for filtering of ultrasonic images. Other interesting are of its application is location of suspicious points which are than further processed by other means to investigate the origin of points abnormality.

REFERENCES

[1] F. Russo, "A New Class of Fuzzy Operators for Image Processing: Design and Implementation". *In Proceedings of Second IEEE International Conference on Fuzzy Systems, FUZZ-IEEE'93*, San Francisco, CA, USA, March 28 - April 1, 1993, pp.815-820.

[2] D.R. Hull, H.E. Kautz & A. Vary, "Measurement of Ultrasonic Velocity Using Phase-Slope and Cross-Correlation Methods". *Materials Evaluation*, vol. 43, no. 11, 1985, pp. 1455-1466.

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[4] W. Sachse & Y.H. Pao, "On the Determination of Phase and Group Velocities of Disperse Waves in Solids", *Journal of Applied Physics*, vol. 49, no. 8, 1978, pp.4320-4327.

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APPENDIX - ULTRASONIC PROPERTIES

Notation

t - time.
f - frequency.
$b_1(t)$, $b_2(t)$ - First and second back surface reflection.
$B_1(f)$, $B_2(f)$ - Fourier transforms of first and second back surface reflections.
X - sample thickness.

Phase Velocity

$$v(f) = \frac{(2X)2\pi f}{arg(B_1(f)) - arg(B_2(f))} \qquad (9)$$

where $arg(B(f))$ is an argument of Fourier transform of pulse B(t).

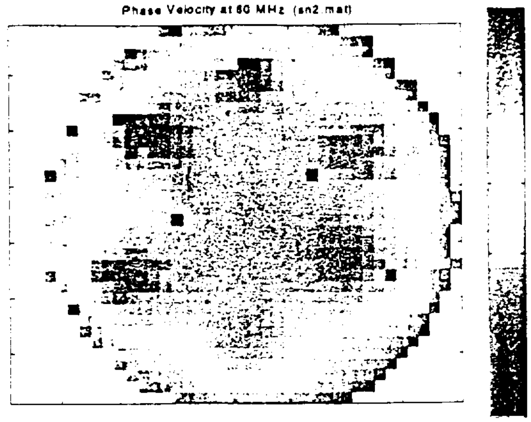

Figure 1: Raw ultrasonic image.

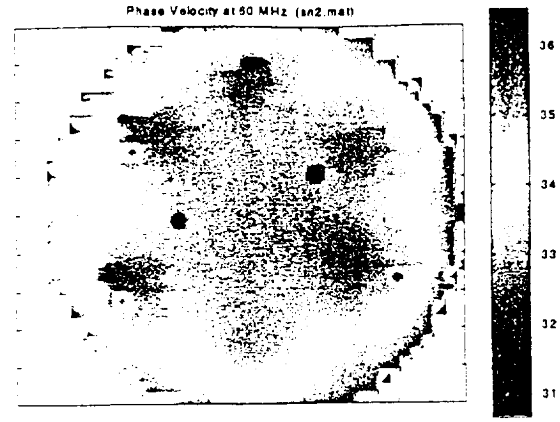

Figure 2: Enhanced raw image.

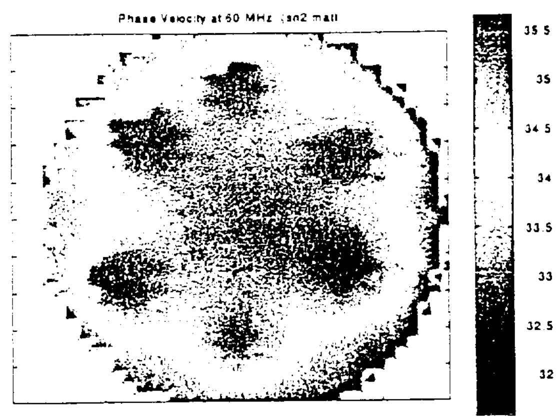

Figure 3: Raw image filtered than enhanced.

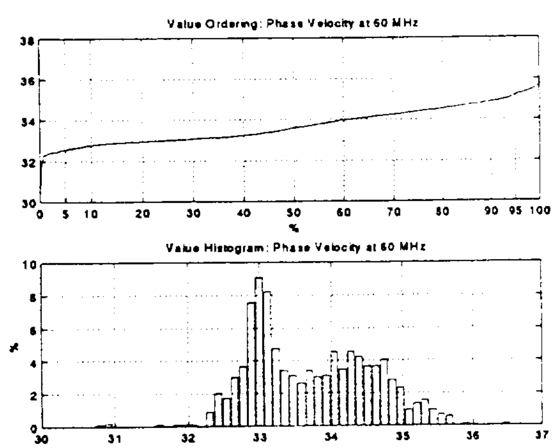

Figure 4: Intensity value histogram.

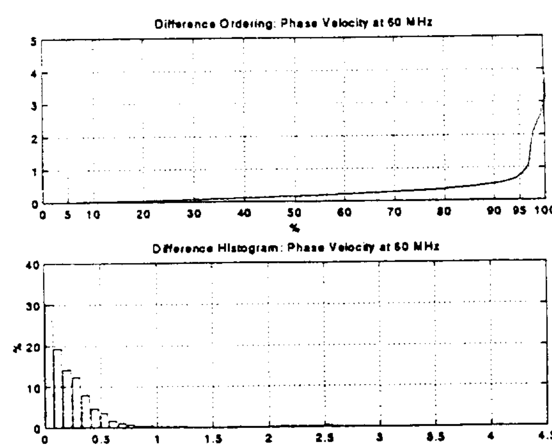

Figure 5: Intensity difference histogram.

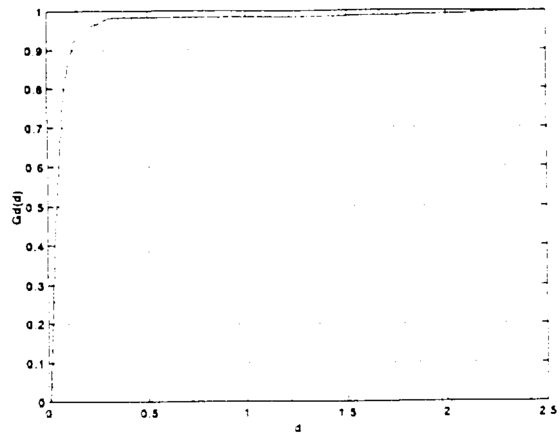

Figure 6: Fuzzy set: *high-intensity-difference.*

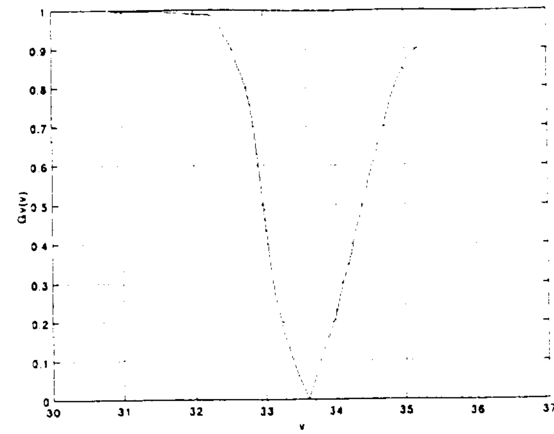

Figure 7: Fuzzy set: *unaverage-intensity-value.*

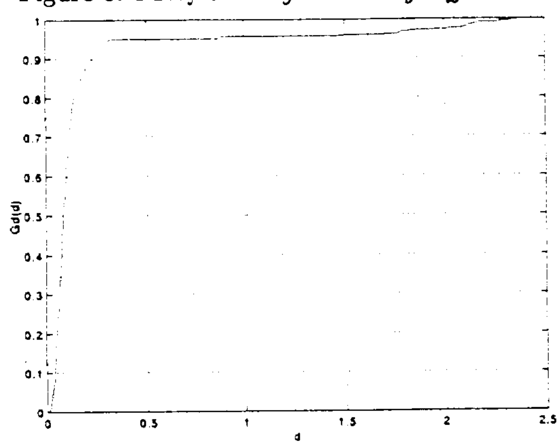

Figure 8: Fuzzy set: very *high-intensity-difference.*

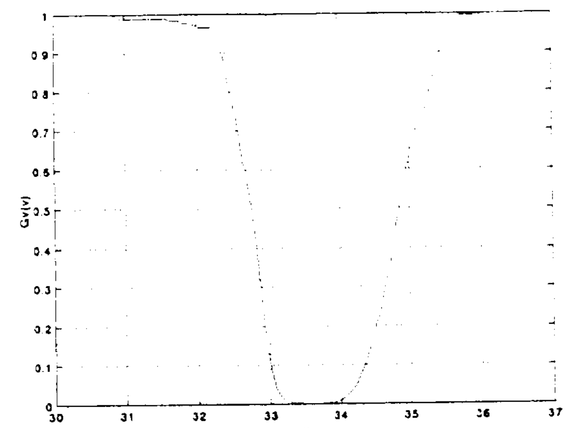

Figure 9: Fuzzy set: very *unaverage-intensity-value.*

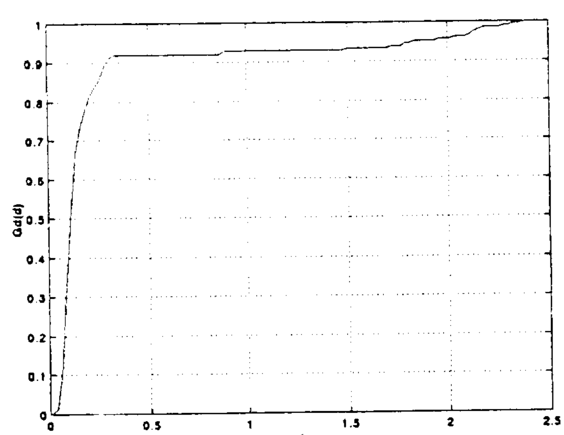

Figure 10: Fuzzy set: extremely *high-intensity-difference.*

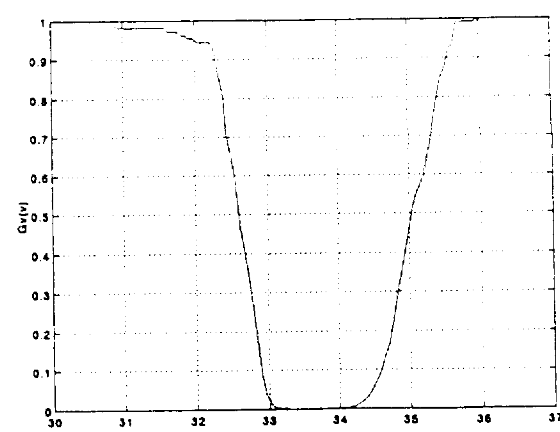

Figure 11: Fuzzy set: extremely *unaverage-intensity-value.*

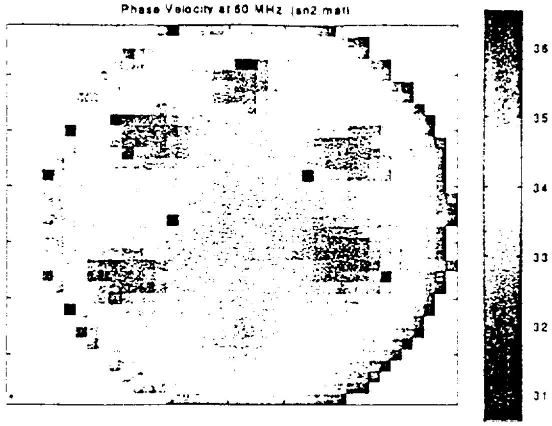

Figure 12: Confidence 0.99, marked 1 point.

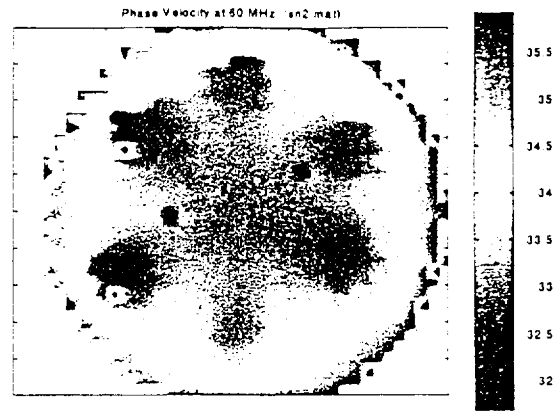

Figure 13: Confidence 0.99, filtered out 1 point.

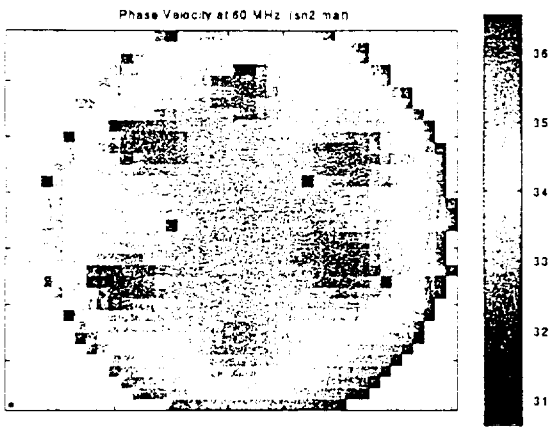

Figure 14: Confidence 0.95, marked 5 points.

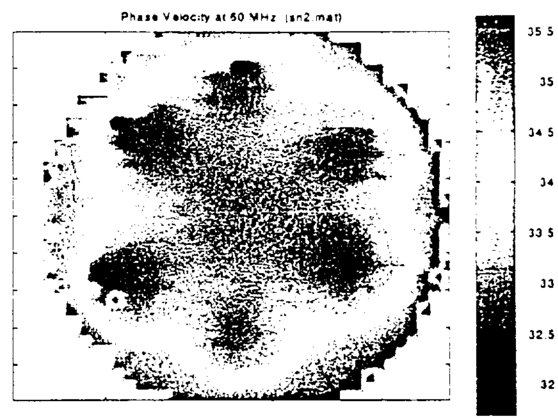

Figure 15: Confidence 0.95, filtered out 5 points.

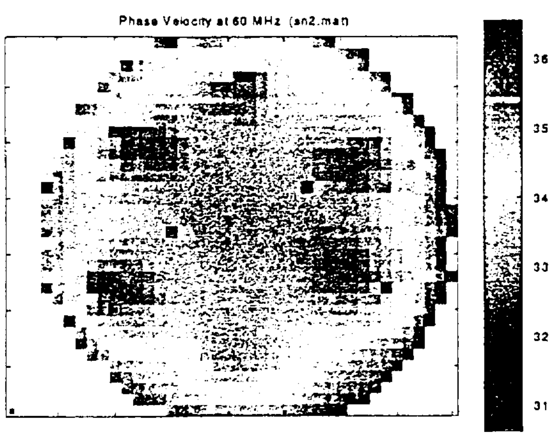

Figure 16: Confidence 0.90, marked 8 points.

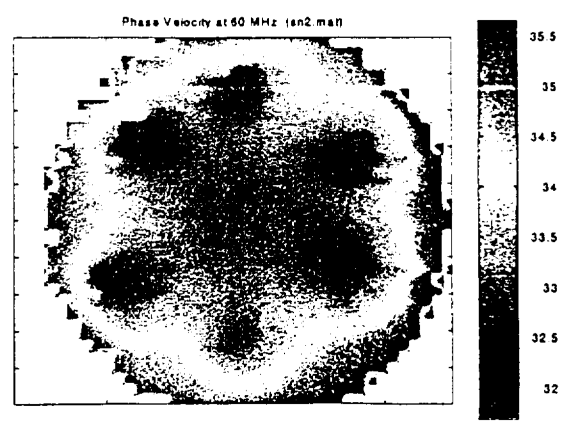

Figure 17: Confidence 0.90, filtered out 8 points.

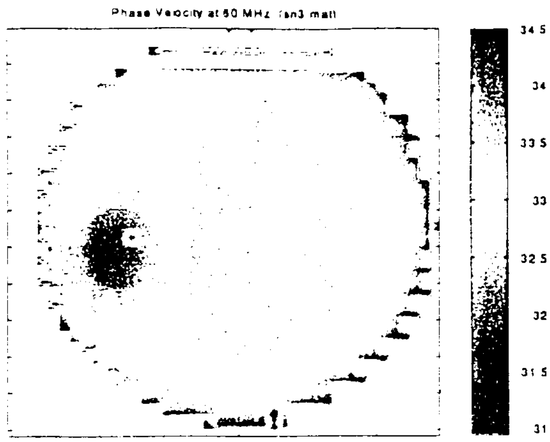

Figure 18: SN3: Raw enhanced.

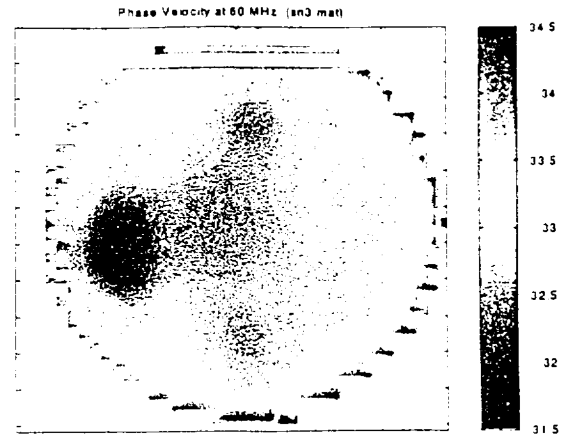

Figure 19: Confidence 0.9, filtered out 7 point.

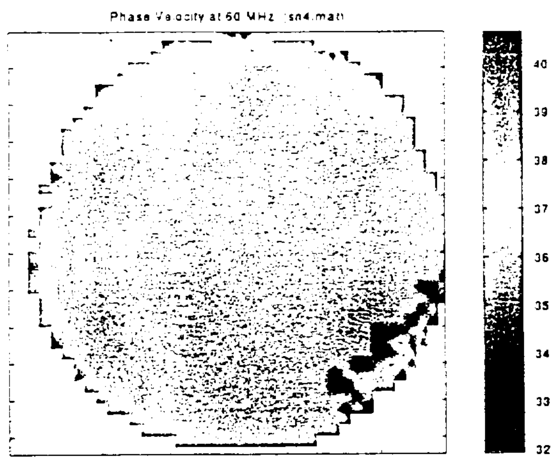

Figure 20: SN4: Raw enhanced.

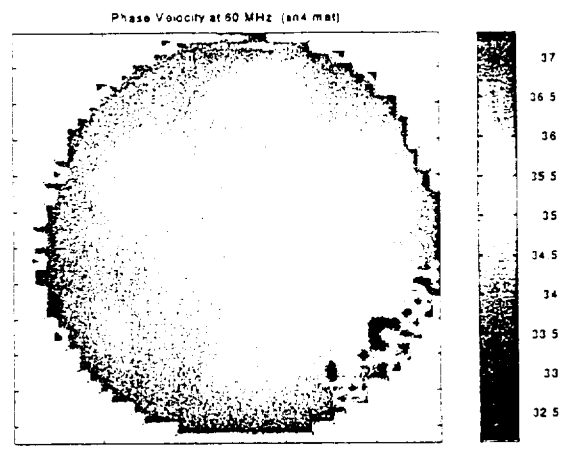

Figure 21: Confidence 0.9, filtered out 10 point.

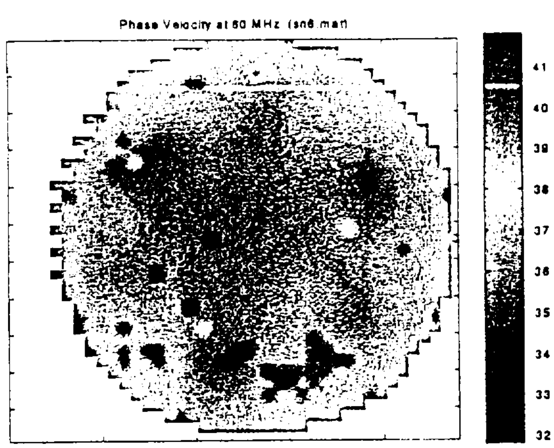

Figure 22: SN6: Raw enhanced.

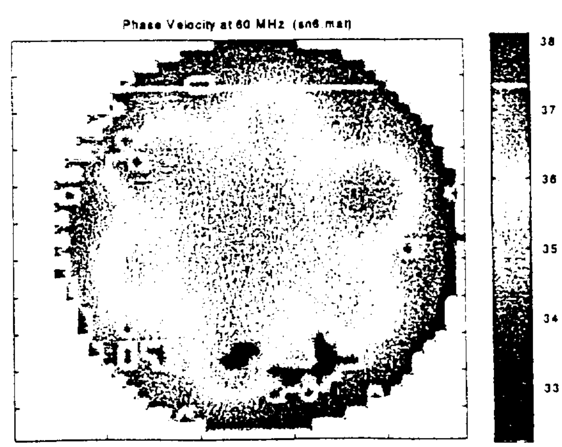

Figure 23: Confidence 0.90, filtered out 9 points.