# Pixel-Level Fuzzy-Logic
# Image-Processing
# Applied to Range-Only-Radar Signals

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## NAVAL AIR WARFARE CENTER WEAPONS DIVISION
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# Naval Air Warfare Center Weapons Division

## FOREWORD

This report documents research performed at the Naval Air Warfare Center Weapons Division (NAWCWPNS), China Lake, California, in the Target-Recognition Section (Code 452320D) as part of an investigation of learning fuzzy expert systems. The work was performed during fiscal year 1997 as part of the Office of Naval Research Independent Research Program.

This report was reviewed for technical accuracy by Mr. Scott Gordon.

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**13. ABSTRACT** *(Maximum 200 words)*

(U)  This report documents work in progress on fuzzy expert systems. Pixel-level fuzzy-logic image-processing (PIXLFLIP) uses fuzzy logic on subwindows centered on each pixel of an image to determine the processing or filtering associated with the center pixel of the subwindow. Here, the PIXLFLIP is applied to enhance range-only-radar (ROR) profiles that have been stacked to produce an image chip. Because the profiles have been aligned by previous processing, the line enhancement needs only to consider vertical lines. The fuzzy, rule-based filtering not only enhances the strong consistent signals, but also suppresses the clutter forming the background. This approach offers significant potential. Further investigation is recommended.

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# INTRODUCTION

This report documents research performed at the Naval Air Warfare Center Weapons Division (NAWCWPNS), China Lake, California, in the Target-Recognition Section (Code 452320D) as part of an investigation of learning fuzzy expert systems. This research is an application of fuzzy logic to image processing at the pixel level, a simple yet powerful concept that is referred to as pixel-level fuzzy-logic image-processing (PIXLFLIP). The application is detecting single masts using high-resolution range-only-radar (ROR) profiles that have been collected into blocks of signal vectors for detection purposes. Within each block, the signals are aligned. Developers have long thought that instead of processing these signal blocks as a sequence of signal profiles, one might also process them as image chips (ICs) and detect and match patterns in this representation as well. This way, developers can easily see and classify these ICs when the statistical classifiers applied to the collection of one-dimensional classifiers fail. In part, humans cue on the signal alignment, which produces strong vertical edges in the IC when detecting a single mast.

Because the human eye is capable of quantifying the stability, shape, and strength-consistency of edges in an image, researchers thought, "Why not try to enhance the features that humans use as visual clues?" The "curse of dimensionality" precludes direct application of statistical pattern recognition to the entire IC; however, after enhancement, classical pattern recognition can be applied to the stacked signal vectors making up the image. Specific special cases that the eye can identify might also be captured by a sequence of fuzzy image-processing rules. This report presents a small example of the power of PIXLFLIP to enhance the ICs by using the special properties of the target signals, and, at the same time, suppressing the clutter and increasing the distinctions to the confusion class signals. This research is an initial exploratory effort supported with very limited independent research funds, which indicates the strong potential of processing the ROR returns as ICs rather than just a group of profiles.

# BACKGROUND

Applying fuzzy modeling to image processing is not new, a fact that Pal and King (Reference 1) were quick to realize. PIXLFLIP is more recent, circa 1994. Russo and Ramponi appear to be the first authors to apply fuzzy logic to construct edge detectors (References 2 through 7), and shortly thereafter, Krishnapuram and Choi used fuzzy logic for line enhancement (References 8 through 12). This approach was modified for the enhancement of the ROR ICs considered in this report. The main concept of PIXLFLIP is best described by an operational definition. Each pixel of the digital image is determined by a set of fuzzy rules that uses the neighbors of that pixel as antecedents to the rule-base (Reference 5). This concept is hardly new if the simple mathematical operations achieved by fuzzy rules are examined. For example, replacing the central pixel by the average of all the pixels in a 3 by 3 window centered at the pixel is just a smoothing operation or low-

pass filter. The difference is the representation and implementation of the fuzzy rules using term sets to determine the firing strength for each of these rules. The fuzzy rules are inherently nonlinear, more intuitive and trainable. In addition, not only can multiple tasks can be captured in a single rule-base, but the processing can also be made adaptive by incorporating the local geometry of the image into the rules themselves (Reference 4).

As an example of PIXLFLIP, consider an edge detector proposed by Russo (Reference 5). A standard image-processing edge detector is the Sobel operator, which is a discrete spatial derivative used to detect an edge and measure its strength. An edge detector is also modeled as a high- or band-pass filter, in contrast to a low-pass filter, which is good at detecting relatively slowly varying regions. Russo cleverly implements the edge detector as the complement of the low-pass filter by using a set of rules or rule-base: " ... to make white the pixels of the image that are surrounded by pixels of similar intensity and to make black all the other ones (the edge pixels)" (Reference 5). So, if the window of interest is 3 by 3, and we model the gray-scale levels by three linguistic levels—LOW, MED, and HIGH—then the rules for the detector have eight antecedent clauses and a hard conclusion of either WHITE or BLACK. The window associated with the rule is given in Figure 1.



FIGURE 1. Inputs for the Edge-Detection Fuzzy Rules.

Rule 1: *If* A1 is LOW & ...& A8 is LOW ==> A9 = WHITE
Rule 2: *If* A1 is MED & ...& A8 is MED ==> A9 = WHITE
Rule 3: *If* A1 is HIGH & ...& A8 is HIGH ==> A9 = WHITE
         ELSE ==> A9 BLACK

Antecedent aggregation or propagation of certainty to the consequent, certainty of the else rule, and the defuzzification determine the value of the center pixel level A9. For definiteness, assume antecedent aggregation is the product and that $\mu_i = \prod_{j=1}^{8} \mu_{x_i}(A_j)$ for the $i$-th rule, $i = 1, 2, 3$ where $x_i$ is LOW, MED, and HIGH, respectively. The else statement certainty is $\mu_4 = \mu_{else} = 1 - \max_i(\mu_i)$. The value of A9 can be determined by any number of

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methods, but assume the defuzzification is just the average $A9 = \sum_{i=1}^{4} \mu_i y_i \Big/ \sum_{i=1}^{4} \mu_i$ where $y_i$ is WHITE for $i = 1, 2, 3$ and BLACK for $i = 4$ (Reference 8).

This hypothetical example was chosen to illustrate the concept of antecedent aggregation and defuzzification. Note that unless one of the first three rules fires strongly, the output pixel is nearly black, indicating the presence of an edge. To determine the memberships, we need the linguistic variables LOW, MED, HIGH, BLACK, and WHITE. The latter two linguistic variables are crisp values, taking on the lowest (BLACK = 0) and highest (WHITE = 255) values of the gray-scale level, here assumed to be defined as [0, 255]. We defined the LOW, MED, and HIGH variables by term sets in Figure 2.
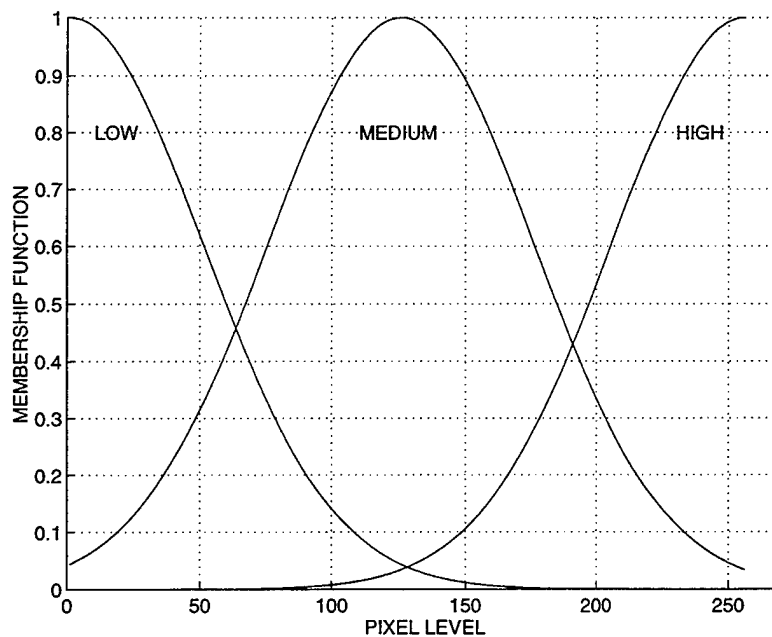


FIGURE 2. Linguistic Variables for the Edge-Detection Fuzzy Rules.

## VERTICAL LINE ENHANCEMENT

Vertical line enhancement using PIXLFLIP has the same structure as the previous example for detecting edges, but with more rules. One advantage of this representation is that the intuitive description of the rules is closer to their implementation. In trying to mimic how humans perceive an edge, the rules model the difference in pixel level between the centerline and its surround, which is defined here to be lines on either side of this bright centerline. To quantify this pixel difference, a linguistic variable defined by its term set NEG for negative is described in Figure 3. To refine this model, not only is the difference between the centerline and its surround used as inputs to the fuzzy rule, but also the pixel-

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level of the centerline. Then the rule consequent not only reflects the presence of a centerline but also its strength. The thirteen fuzzy rules used for this model are contained in Appendix A along with the fourteenth rule, which is the default fuzzy rule. A typical fuzzy rule is as follows:

Rule 10: *If* A1 is ORANGE & A2 is NEG & A3 is NEG ==> ORANGE

where

ORANGE is a linguistic variable representing the pixel level of the centerline

NEG is the linguistic variable that tests the contrast between the centerline and its two surrounding lines

This rule is a single-line rule where A1 represents the average of the centerline, A2 is the difference between the average of the left-surround line and A1, and A3 is the difference between the average of the right-surround line and A1. The linguistic variables are illustrated in Figure 4.
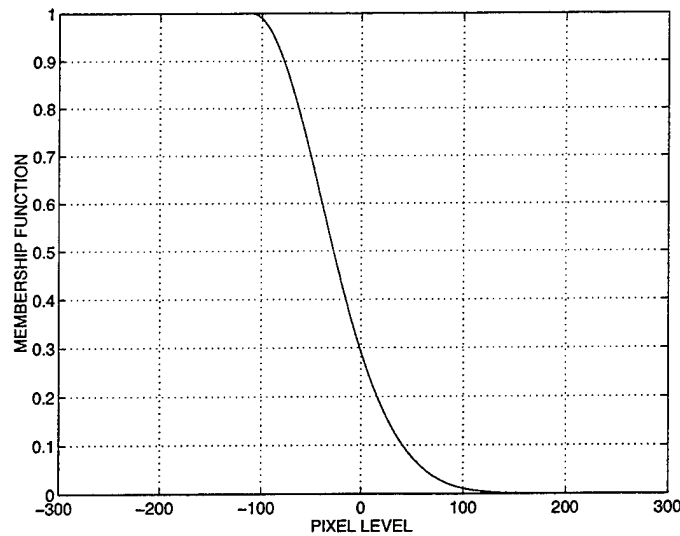


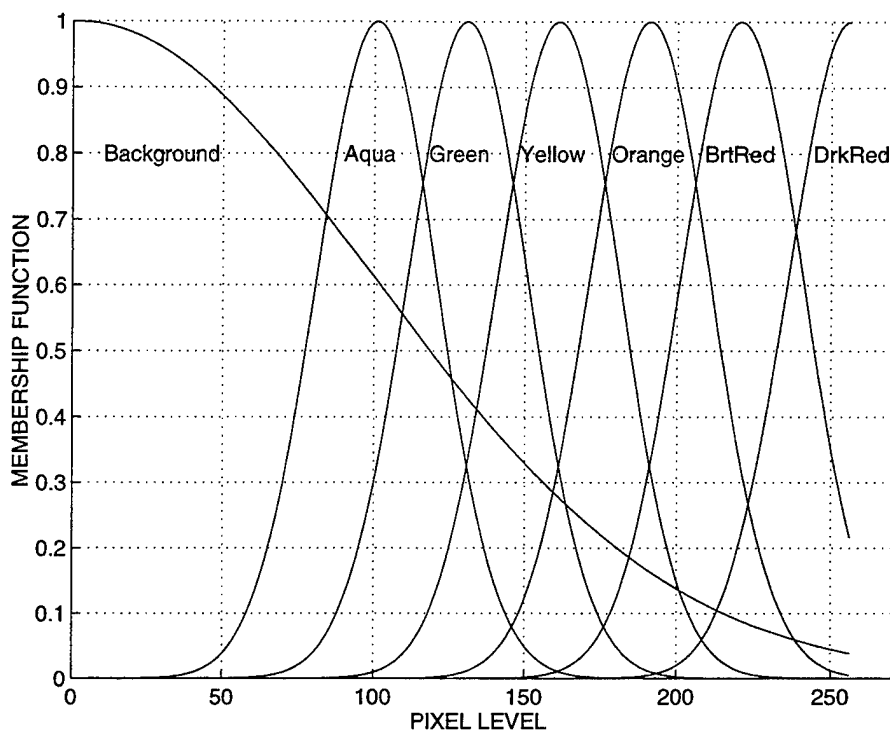FIGURE 3. The Linguistic Variable NEG.

FIGURE 4. Linguistic Variables For Line Enhancement.

So, the input features are constructed from average pixel levels formed over columns that are either part of the centerline or its surround. The columns used for A1 depend on the centerline width, either one or two pixels. Double-line fuzzy rules have some redundancy because a double line cannot be centered with respect to a single-center pixel of the 5 by 5 window. A typical pair of rules is as follows:

Rule 5: *If* A1 is YELLOW & A2 is NEG & A3 is NEG ==> YELLOW
Rule 6: *If* A1' is YELLOW & A2' is NEG & A3' is NEG ==> YELLOW

The columns averaged are different for these two rules. For example, A3 and A3' are averages of different columns. The definitions for these rules are in Appendix A.

Implementation of the rule-base follows (Reference 7). Each antecedent clause is implemented by using Ai or Ai' to obtain the degree of membership into the linguistic term. For example, certainty of A1 is YELLOW is evaluated by using $\mu_{Yellow}(A1)$, and the entire certainty of the consequence for the sixth rule is given by

$$\mu_{C6} = \mu_{Yellow}(A1) * \mu_{Neg}(A2) * \mu_{Neg}(A3).$$

The certainty of the alternative hypothesis is

$$\mu_{14} = 1 - \max_{i<14}(\mu_i).$$

Defuzzification obtains by using a crisp representative value for each consequent variable, denoted by $y_i$.

The final pixel value given to the center of the window is

$$y = \sum_{i=1}^{N} \mu_i y_i \Big/ \sum_{i=1}^{N} \mu_i$$

where

$N$ is the number of rules or 14 in this example.

## RADAR EXAMPLES

The line-enhancement program was applied to high-resolution ROR data that were stacked and aligned in blocks of 25 profiles of length 16. Several examples are given in Appendix B. Returns from objects with the most spatial stability and the most consistent return strength produced the cleanest signals. For the stable single mast, the object appeared as a strong double line in the IC surrounded by clutter. Vertical-line enhancement suppressed the clutter, because clutter seldom produced a consistent stable return. Effectively, the fuzzy rules produced a spatially local vertically oriented time-averaging filter that reduced clutter. Signals that were spatially unstable or temporally inconsistent or consistently weak fired the default rule most often, producing the black background signals, which suppressed the clutter. Moreover, strong signals that were spatially unstable and time varying produced inconsistent single and double lines, which were weak in response and located away from the center of the IC. This process increased the distinction between the stable single-mast IC. Notice, too, that signal dropouts—those rows that appear blank—were discarded from the IC, which was a weak attempt to eliminate the effect of single- and double-line dropouts on the fuzzy rules because humans tend to ignore these small dropouts when classifying objects from the IC.

Appendix B contains some examples of line enhancement on several different classes of objects that have different spatial extent, stability, and consistency. Each figure contains the original IC and two passes of line enhancement. Hundreds of ICs exist for each class available for testing. Figure B-1 contains the most interesting signal, a stable consistently strong single mast. Figures B-2 through B-6 are some of the confusion classes. If the goal is to accentuate the difference between the single-mast IC, these figures indicated that the first pass helps that effort, but the second pass erased the differences. From a real-time prospective, that is good. Concentrating on the first-pass results, all the classes had a double line in the center of the IC, but only the first class had a strong consistent double centerline, with virtually no anomalous lines or streaks in the surround. Ideally, if this fact holds true for the vast majority of ICs, a classifier can distinguish between the first class and all other confusion classes. To test this concept in practice, we must take thousands of these ICs s, construct a classifier, and determine the error rates.

## CONCLUSIONS

The unqualified conclusion of this research is that the PIXLFLIP holds significant potential to extract the signal and scrub the clutter in the ROR ICs. The qualification is that the algorithm was only to be tested on a few hundred ICs and needs to be tested on thousands of ICs. Moreover, a classifier should be built to quantify any improvement in signal extraction and noise suppression. However, this effort is being funded on limited IR funds, and such a study is not within the scope of this exploratory work.

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## Appendix A

## THE FUZZY RULES

The fuzzy rules are partitioned into two groups: single-line enhancement and double-line enhancement. In addition, there is a default rule. The total number of rules is 14: eight double-line rules, five single-line rules, and one default rule. In the following rules, capitalized terms are linguistic variables that represent termsets on the pixel levels. Each fuzzy rule has three antecedents. The inputs to the antecedents are constructed on 5 by 5 windows by averaging columns of pixels. The first antecedent tests the average strength of the central strip, the second tests the relative strength of the central strip with respect to the left-hand-side strip, and the third tests the relative strength with respect to the right-hand-side strip. Figure A-1 shows this configuration, where the columns used to construct the inputs are hatched for the single-line rules. The variable A1 is the average of the pixel values in the central column illustrated by the first window. A2 is the difference between the average of the pixels in the first column (see the second window of Figure A-1) and the variable A1. Finally, A3 is the difference between the average of the pixels in the fifth column (see the third window of Figure A-1) and the variable A1.
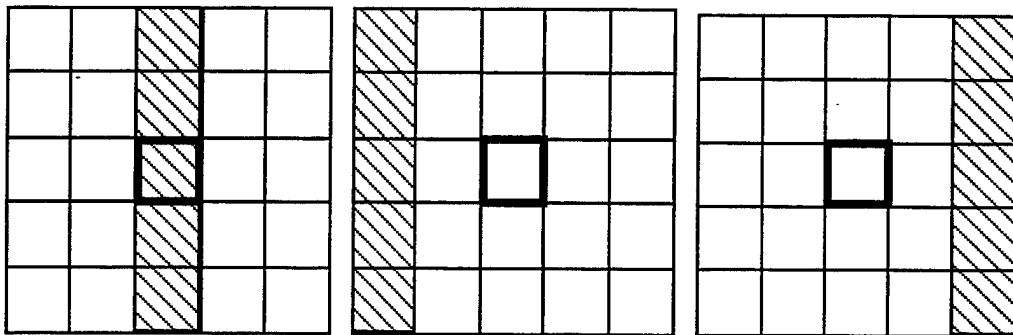


FIGURE A-1. Single-Line Rules and Columns Needed To Construct A1, A2, and A3, Respectively.

In the double-line rules, two of the central columns are averaged to obtain the first input and then subtracted from the averaged column on the left and the averaged column on the right to generate the second two inputs. For these rules, two definitions for input features are needed because of the two possible positions of the double line with respect to the center of the data window.

Figures A-2 and A-3 define the columns over which the averages are taken for the two sets of rules. Again, the hatched columns represent the pixel values that are averaged to construct the variables, which should explain to the reader why rules appear to be duplicated. However, the rules are different because the average is taken over different columns. Conceptually, the two sets of rules are doing the same thing but compensating for the centering ambiguity of the double line. Presence of strong central pixels and weak

adjacent pixels tend to trigger the rules. The strength of the conclusion is given by the product of the degrees that the antecedents are satisfied. The input values are

A1 = average pixel value of the central strip or strips
A2 = average pixel value of the left-hand-side strip - A1
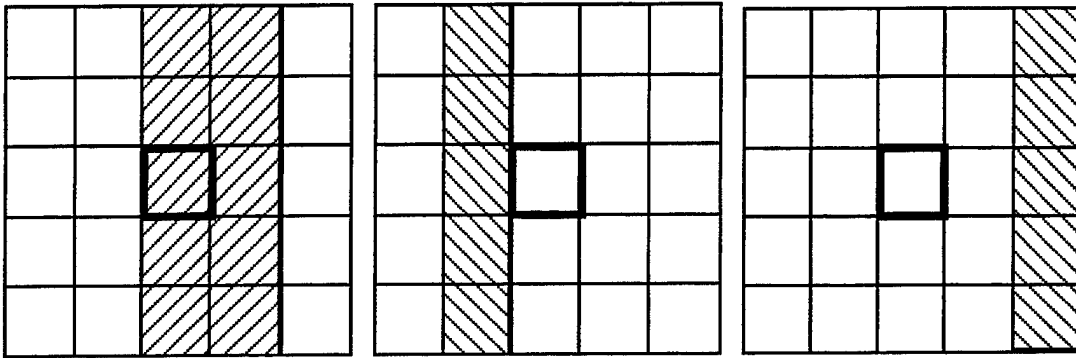A3 = average pixel value of the right-hand-side strip - A1

Likewise,

A1' = average pixel value of the central strip or strips
A2' = average pixel value of the left-hand-side strip - A1'
A3' = average pixel value of the right-hand-side strip - A1'



FIGURE A-2. First Type of Double-Line Rule and Columns Needed To Construct A1, A2, and A3, Respectively.



FIGURE A-3. Second Type of Double-Line Rule, Columns Needed To Construct A1', A2', and A3' Respectively.

The first eight rules are double-lined rules. There are two sets of rules; the first rule corresponds to the window's central pixel being in the first column of the double strip, and the second rule has the central pixel in the second column of the double line. Both cases must be included to detect a double line in the window.

**Double-Line Rules**

Rule 1:  *If*  A1 is BRTRED & A2 is NEG& A3 is NEG ==> DRKRED
Rule 2:  *If*  A1' is BRTRED& A2' is NEG& A3' is NEG ==> DRKRED
Rule 3:  *If*  A1 is ORANGE & A2 is NEG & A3 is NEG ==> ORANGE
Rule 4:  *If*  A1' is ORANGE &  A2' is NEG & A3' is NEG ==> ORANGE
Rule 5:  *If*  A1 is YELLOW & A2 is NEG & A3 is NEG ==> YELLOW
Rule 6:  *If*  A1' is YELLOW& A2' is NEG& A3' is NEG ==> YELLOW
Rule 7:  *If*  A1 is GREEN & A2 is NEG & A3 is NEG ==> GREEN
Rule 8:  *If*  A1' is GREEN & A2' is NEG& A3' is NEG ==> GREEN

**Single-Line Rules**

Rule 9:   *If* A1 is BRTRED & A2 is NEG & A3 is NEG ==> BRTRED
Rule 10: *If*  A1 is ORANGE & A2 is NEG & A3 is NEG ==> ORANGE
Rule 11: *If* A1 is YELLOW & A2 is NEG & A3 is NEG ==> YELLOW
Rule 12: *If* A1 is GREEN & A2 is NEG& A3 is NEG ==> GREEN
Rule 13: *If* A1 is AQUA & A2 is NEG & A3 is NEG ==> AQUA

**Default Rule**

Rule 14: *Else*  ==> BACKGROUND

The linguistic variables are defined by term sets illustrated in Figure 4 (repeated in Figure A-4 for the reader's convenience).
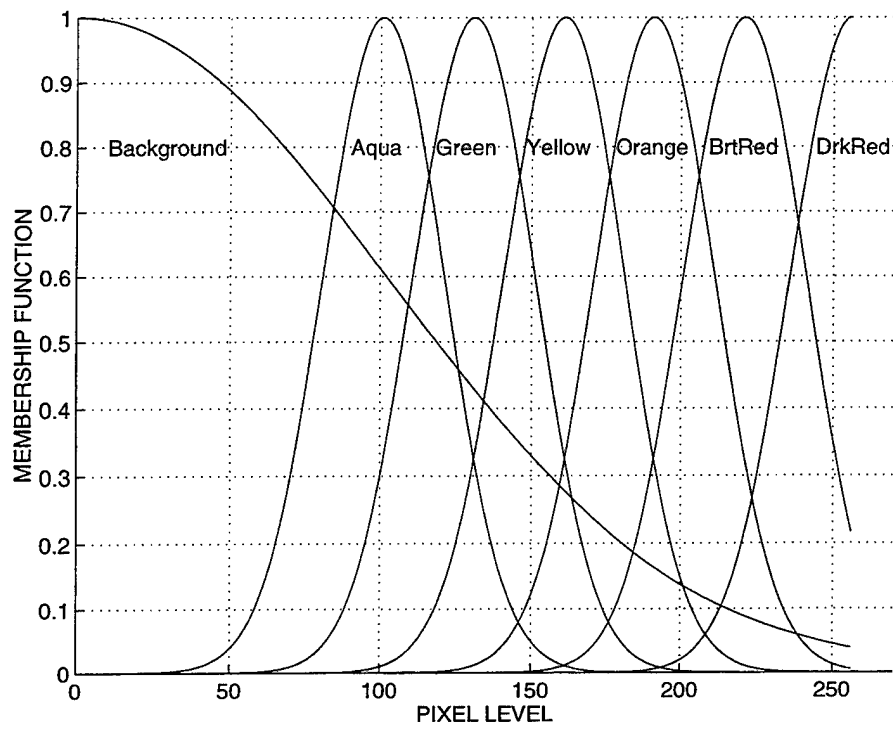
FIGURE A-4. Linguistic Variables for Line Enhancement.

# Appendix B

# THE RESULTS

This appendix discusses several alternate classes of data that were processed with the fuzzy line enhancement. Placing these data in one section makes it is easier for the reader to compare the results.
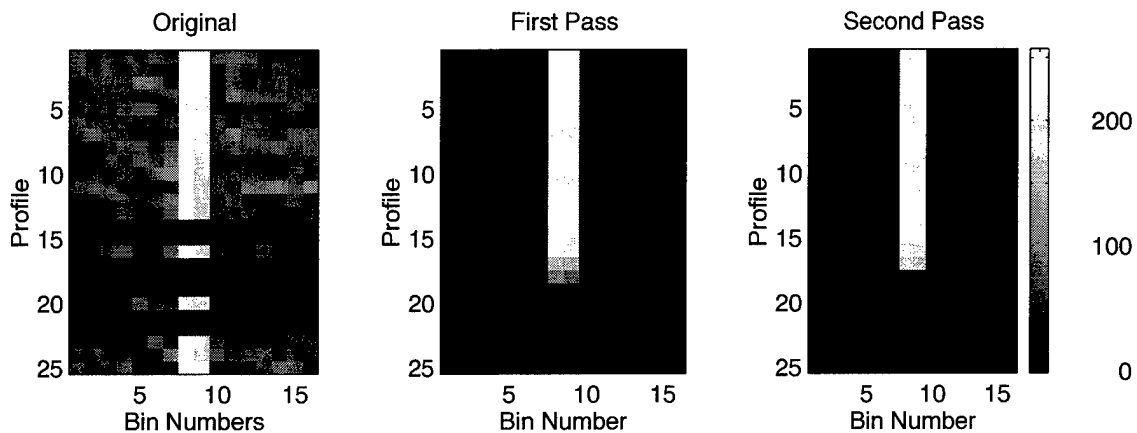


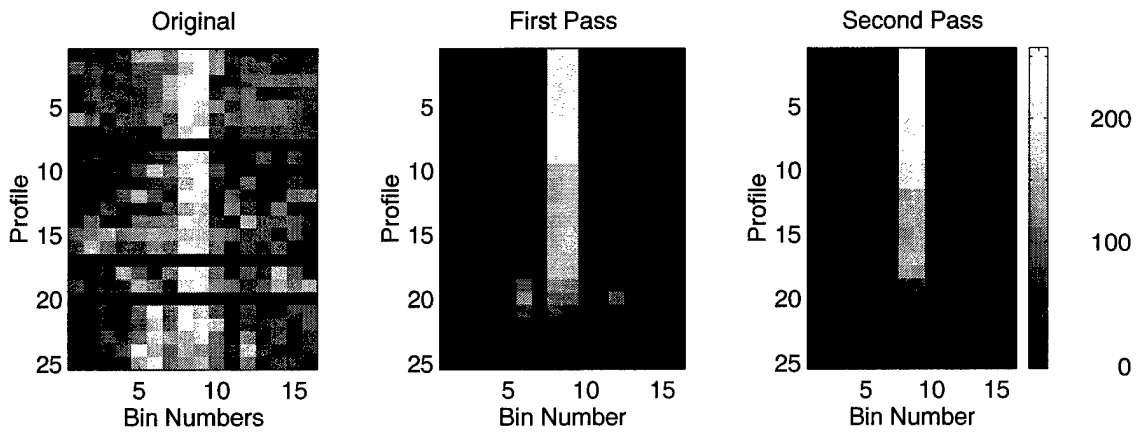FIGURE B-1. A Single Mast in Clutter, Moderately Weak Signal.
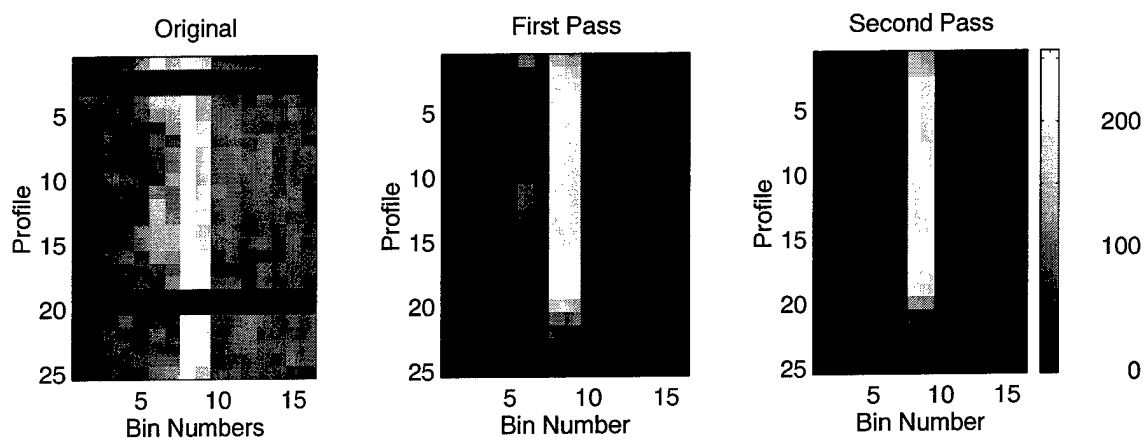


FIGURE B-2. A Strong Consistent Confusion Class.

Original
First Pass
Second Pass

FIGURE B-3. A Second Strong Consistent Confusion Class.
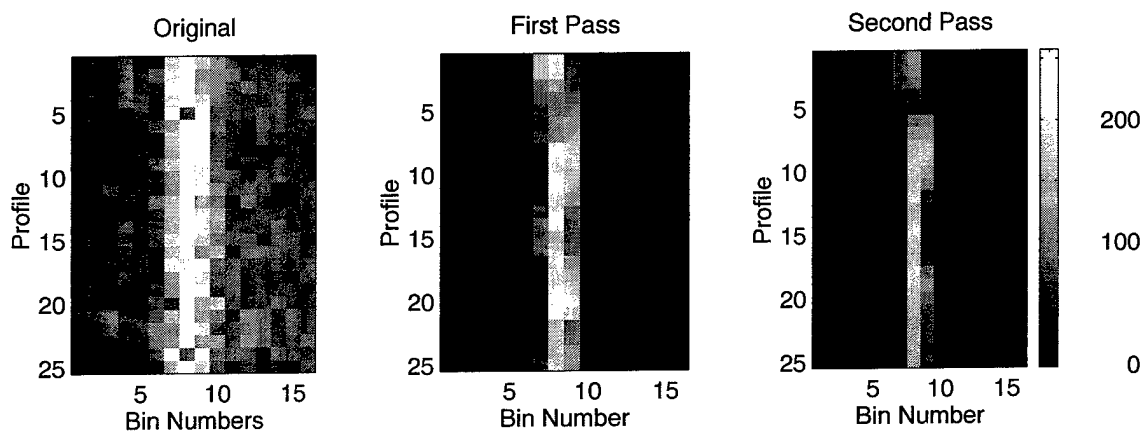
Original
First Pass
Second Pass

FIGURE B-4. A Third Strong Consistent Confusion Class.
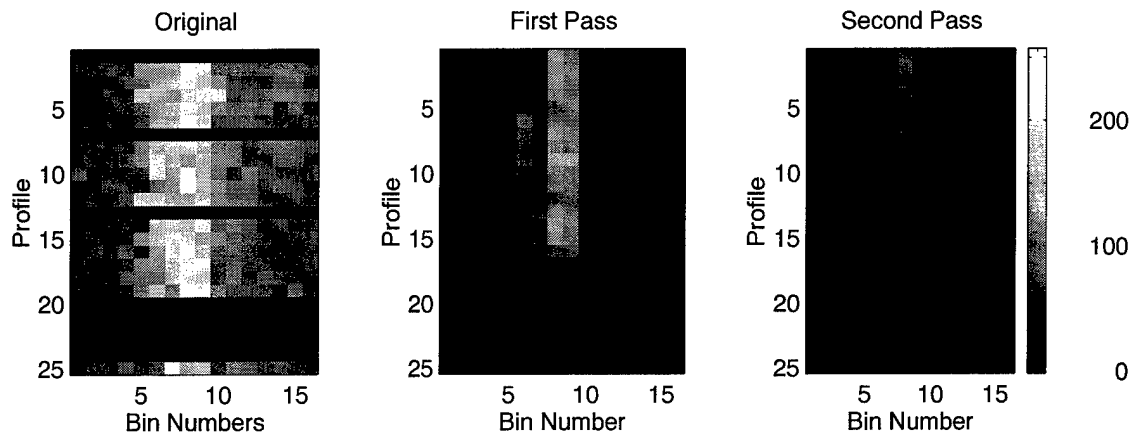
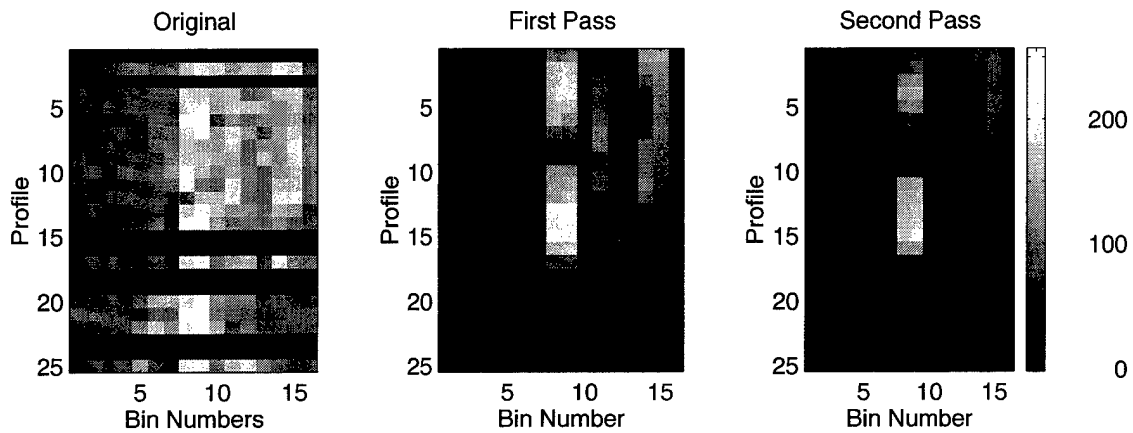FIGURE B-5. A Fourth Consistent Confusion Class.



FIGURE B-6. A Fifth Strong Confusion Class.

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