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STRUCTURAL PATTERN RECOGNITION  
IN SEISMOGRAM ANALYSIS

Kou-Yuan Huang

Clare D. McGillem

Paul E. Anuta

School of Electrical Engineering  
and  
Laboratory for Applications of Remote Sensing  
Purdue University West Lafayette, Indiana 47907 USA  
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West Lafayette, IN 47907, U.S.A.

ABSTRACT

Use of statistical decision techniques and structural pattern recognition can eliminate random noise effects and aid in obtaining consistent layer reflection coefficients. Z, T, likelihood ratio and Chi-squared tests are used in statistical hypothesis testing in the work reported here. The structural patterns used are horizontal and sloping linears. Iterative computation from left to right and right to left in the seismogram was found to improve results.

INTRODUCTION

In the seismogram after deconvolution, the signal-to-noise ratio usually decreases although a spiking filter can restore the wavelet to a spike. Inconsistent reflections occurring as singular noise pulses may exist in the seismogram. A simulated seismogram, reflection coefficients

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plus the Gaussian random white noise with zero-mean, variance  $\sigma^2 = (0.05)^2$ , are described. Techniques for addressing the spatial "boundary finding" problem can be found in [1], [2], [3], [4]. In seismic analysis, the equivalent problem is the "reflection coefficient finding" problem. The Z, T, likelihood ratio and  $\chi^2$  tests are used in the work reported here to find boundary layer reflections. The boundary layer reflections have some structural information so the horizontal pattern and slope pattern are used also.

### HYPOTHESIS TESTING METHODS

#### Method 1: Z- Test

The statistical decision rule is:

$$Z = \left| \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\sqrt{\frac{\sigma_x^2}{N_x} + \frac{\sigma_y^2}{N_y}}} \right| \begin{matrix} > \\ < \end{matrix} \alpha_1 \text{ (threshold)}$$

Where:  $\bar{X}$ ,  $\bar{Y}$  are sample means

$\mu_x = \mu_y = 0$ , population mean of Gaussian noise

$N_x = N_y = 2$  (Two point pairs are selected)

$\sigma_x^2 = \sigma_y^2 = (0.05)^2$

The X point is classified as a reflection or noise by using its neighboring three pairs of points:

1 3

2 x 2

3 1

$Z_1$  is computed from Pair 1 and Pair 2.

$Z_2$  is computed from Pair 2 and Pair 3.

$Z_3$  is computed from Pair 1 and Pair 3.

The hypotheses are:

$H_0$ : No reflection present if  $Z_1, Z_2$  and  $Z_3 < \alpha_1$ .

$H_1$ : Reflection present if  $Z_1$  or  $Z_2$  or  $Z_3 > \alpha_1$ .

If  $H_1$  is satisfied, the testing X point is kept, else the output is zero. The iterative computation proceeds from left to right and right to left in the seismogram. The reflection coefficients plus Gaussian random noise are shown in Figure 1. The classification result is shown in Figure 2. In this method, the value of the reflection coefficient is not used here, i.e., the property of Gaussian noise is used.

Method 2: T- Test

$$T = \left| \frac{(\bar{X} - \bar{Y}) - (\mu_x - \mu_y)}{\left[ \left( \frac{N_x S_x^2 + N_y S_y^2}{N_x + N_y - 2} \right) \left( \frac{1}{N_x} + \frac{1}{N_y} \right) \right]^{1/2}} \right| \begin{matrix} > \\ < \end{matrix} \alpha_2$$

The selected linear (horizontal) pattern is shown below:

\*\*\* X \*\*\*

X - testing point

            
7 points

A 7-point linear neighborhood is used for  $\bar{Y}$ . The first 15 points from the first line represent noise and  $\bar{X}$  is calculated from these samples.

So:  $N_x = 15$        $N_y = 7$

$S_x^2 =$  Sample variance of 15 point noise

$S_y^2 =$  Sample variance of 7 points

$\mu_x = \mu_y = 0$

The hypotheses are:

$H_0$ : No reflection present if  $T < \alpha_2$ .

$H_1$ : Reflection present if  $T > \alpha_2$ .

The iterative computations are the same as for the Z- test. The signal plus noise is shown in Figure 3 and the testing result is shown in Figure 4. For slope pattern, the testing pattern will be slope. In this method, the value of the reflection coefficient is also not used.

Method 3: Likelihood Ratio Test (LRT) and  $\chi^2$  Test With a Linear Pattern

For the two hypotheses:

$H_1$ :  $\rho_1 = m + n_1$  ,  $i = 1, 2, 3, \dots, N$

$H_0$ :  $\rho_1 = n_1$  ,  $i = 1, 2, 3, \dots, N$

Each noise sample is zero-mean Gaussian with variance  $\sigma^2$ . The noise samples at various instants are independent random variables. The likelihood ratio test (LRT) [5] is:

$$\ln \Lambda(\underline{R}) = \ln \left[ \frac{P(\underline{R}|H_1)}{P(\underline{R}|H_0)} \right] = \frac{\mu}{\sigma^2} \sum_{i=1}^N R_i - \frac{Nm^2}{2\sigma^2} \begin{matrix} > \\ < \end{matrix} \begin{matrix} H_1 \\ H_0 \end{matrix} \ln \eta$$

or, equivalently

$$\sum_{i=1}^N R_i \begin{matrix} > \\ < \end{matrix} \begin{matrix} H_1 \\ H_0 \end{matrix} \frac{\sigma^2}{m} \ln \eta + \frac{Nm}{2}$$

Usually let  $\eta = 1$ , then

$$\sum_{i=1}^N R_i \begin{matrix} > \\ < \end{matrix} \begin{matrix} H_1 \\ H_0 \end{matrix} \frac{Nm}{2}$$

The  $\chi^2$ - test decision rule is

$$\frac{Ns^2}{\sigma_\eta^2} > \alpha_3 \text{ or } \alpha_4 \text{ (threshold)}$$

For the horizontal pattern, N=5 testing points and threshold is  $\alpha_3$ .

X X X X X

~~~~~  
5 testing points

For the slope pattern,  $N=7$  testing points and the threshold is  $\alpha_4$ .

X X X X X X X

7 testing points

with a  $45^\circ$  slope

The reflection coefficient in Figure 5 is  $m=0.2$ . Variance of the Gaussian random noise  $\sigma_n^2 = (0.05)^2$ . The purpose of the  $\chi^2$ -test is to detect the homogeneous content (small variance) in the testing points, i.e., they are all signal. The purpose of LRT is to detect the presence of the signal. The decision procedure is as follows:

Step 1:

$$i=1,2,\dots,512$$

Set matrix  $R(i,j) = 0$

$$j=1,2,\dots,20$$

Step 2:

If the testing patterns are satisfied by LRT, i.e.,

$$\sum_{i=1}^N R_i > \frac{Nm}{2}$$

and by  $\chi^2$ -test, i.e.,

$$\frac{NS^2}{\sigma_n^2} < \text{threshold}$$

then the values of the testing patterns are assigned to  $R(i,j)$  as the new values. Else, move to another testing pattern.

The result of this method is shown in Figure 6.

Method 4: Likelihood Ratio Test and  $\chi^2$ - Test With Block Pattern

The theories are the same as for Method 3, but the testing pattern points are different. Three testing points for every pair are used here:

1 3

2 Y 2

3 1

$N=3$  (including Y)

The decision procedures are as follows:

Test Pair 1 (including Y), using Steps 1 and 2 of Method 3. The same procedures apply for Pair 2 and Pair 3. The result of this method is shown in Figure 7. The detected portion is three points per group.



SUMMARY AND SUGGESTIONS

1. Structural information in a synthetic seismogram was extracted in the presence of additive noise by various classification methods. The consistent reflection coefficients were retained and the random noise eliminated.
2. In comparing the four classification methods, the result of the likelihood ratio and  $\chi^2$ -test with 5-point horizontal pattern and 7-point slope pattern is the best.
3. For more complex seismic reflection, the testing structural pattern will be more complex.
4. This structural pattern recognition is recommended to apply in real seismic data and improve the seismic interpretation.

REFERENCES:

1. Kettig, R.L. and D.A. Landgrebe, "Automatic Boundary and Sample Classification of Remotely Sensed Multispectral Data, LARS Information Note 041773, Laboratory for Applications of Remote Sensing (LARS), Purdue University, West Lafayette, IN 47906-1399. 1973.
2. Gupta, J.N., R.L. Kettig, D.A. Landgrebe, and P.A. Wintz, "Machine Boundary Finding and Sample Classification of Remotely Sensed Agricultural Data," LARS Information Note 102073, LARS, Purdue University. 1973.
3. Kettig, R.L., "Computer Classification of Remotely Sensed Multispectral Image Data by Extraction and Classification of Homogeneous Objects," LARS Information Note 050975, LARS, Purdue University. 1975.
4. Kettig, R.L. and D.A. Landgrebe, "Classification of Multispectral Image Data by Extraction and Classification of Homogeneous Objects, LARS Information Note 062375, LARS, Purdue University. 1975.
5. Van Trees, H.L., "Detection, Estimation, and Modulation Theory," Vol. I. Wiley, New York, NY. 1968. Pp. 23-28.

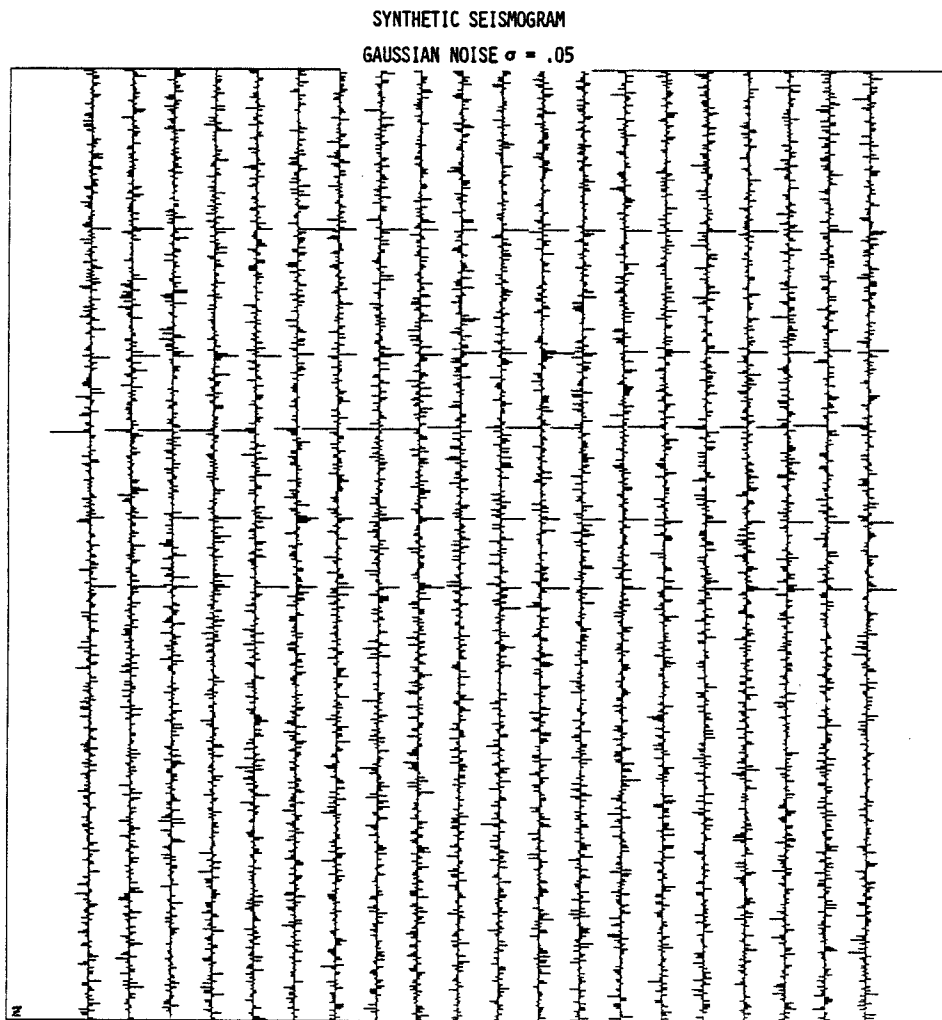


Figure 1. Synthetic Seismogram.  
Gaussian Noise  $\sigma = .05$ .

Z-TEST SPATIAL DECISION RULE

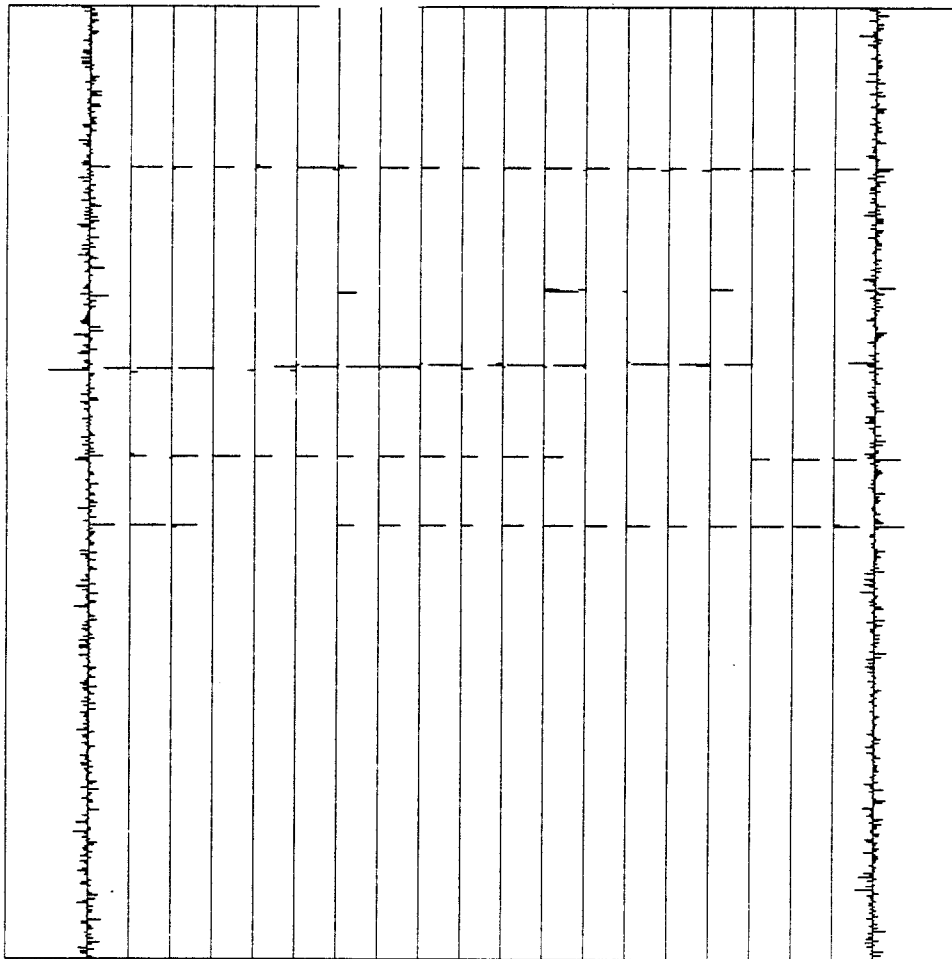


Figure 2. Result of Z- Test Spatial Decision Rule  
(3 patterns, 3-point neighborhood per pattern).

SYNTHETIC SEISMOGRAM  
GAUSSIAN NOISE  $\sigma = .05$

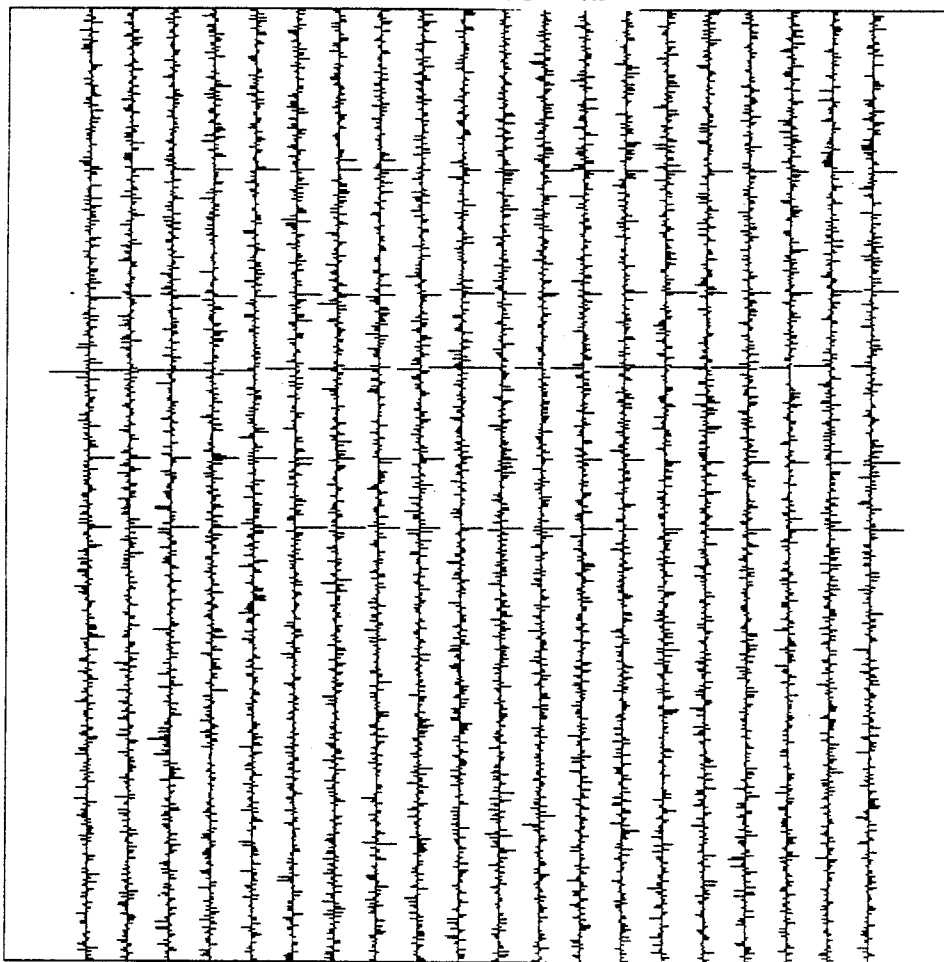


Figure 3. Synthetic Seismogram.  
Gaussian Noise  $\sigma = .05$ .

T-TEST SPATIAL DECISION RULE

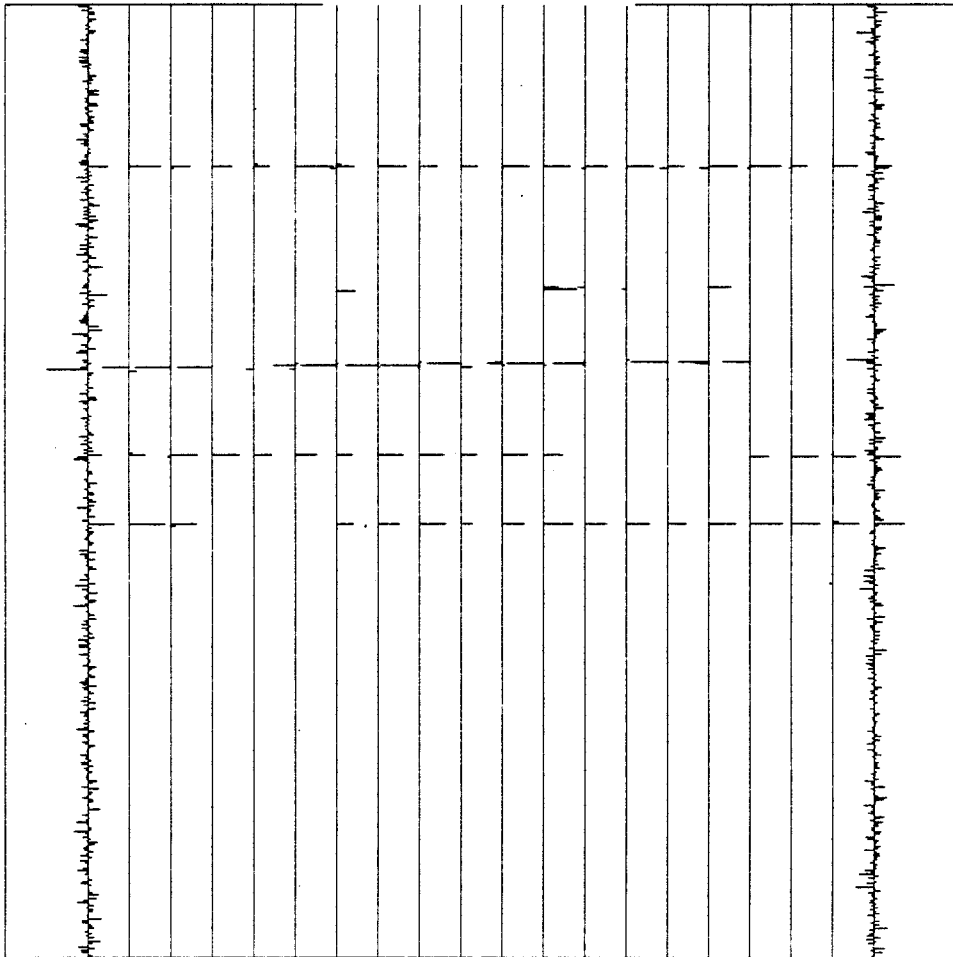
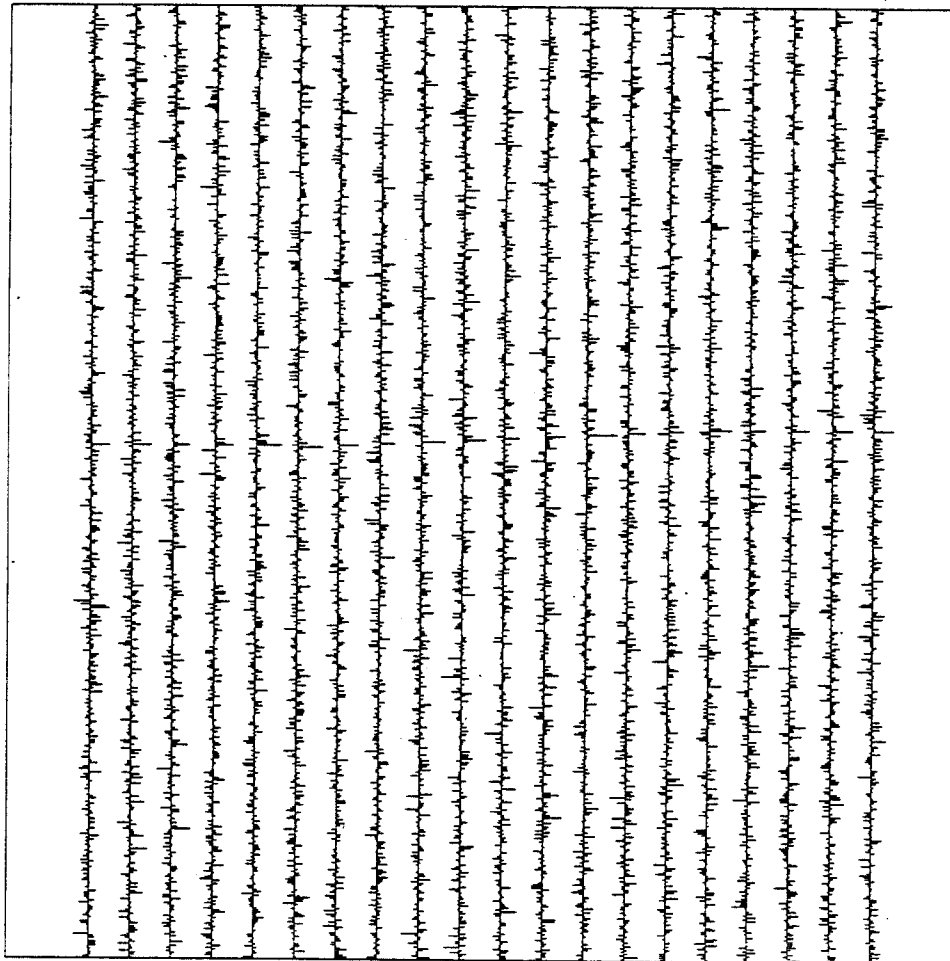


Figure 4. Result of T- Test Spatial Decision Rule (7-point horizontal pattern only).

SYNTHETIC SEISMOGRAM  
GAUSSIAN NOISE  $\sigma = .05$



x7

Figure 5. Synthetic Seismogram.  
Gaussian Noise  $\sigma = .05$ .

$\chi^2$ -TEST SPATIAL DECISION RULE

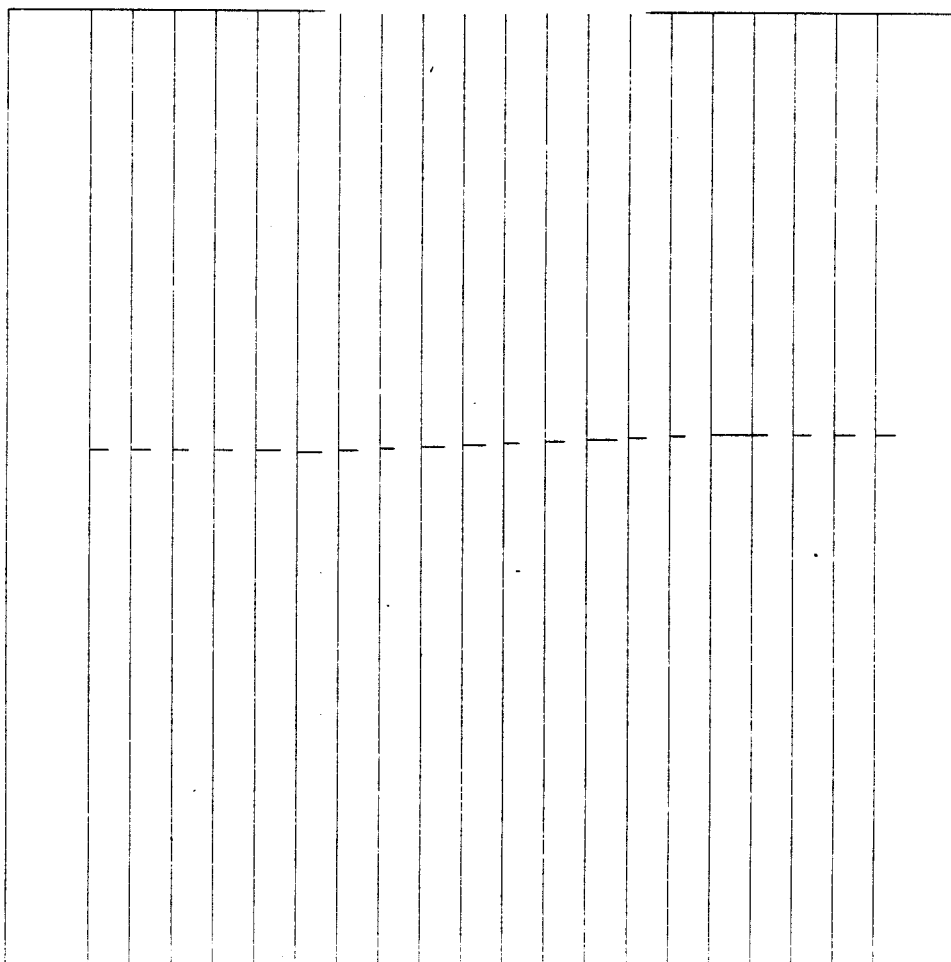


Figure 6. Result of LRT and  $\chi^2$ - Test Spatial Decision Rule (5-point horizontal and 7-point slope patterns are used).



$\chi^2$ -TEST SPATIAL DECISION RULE

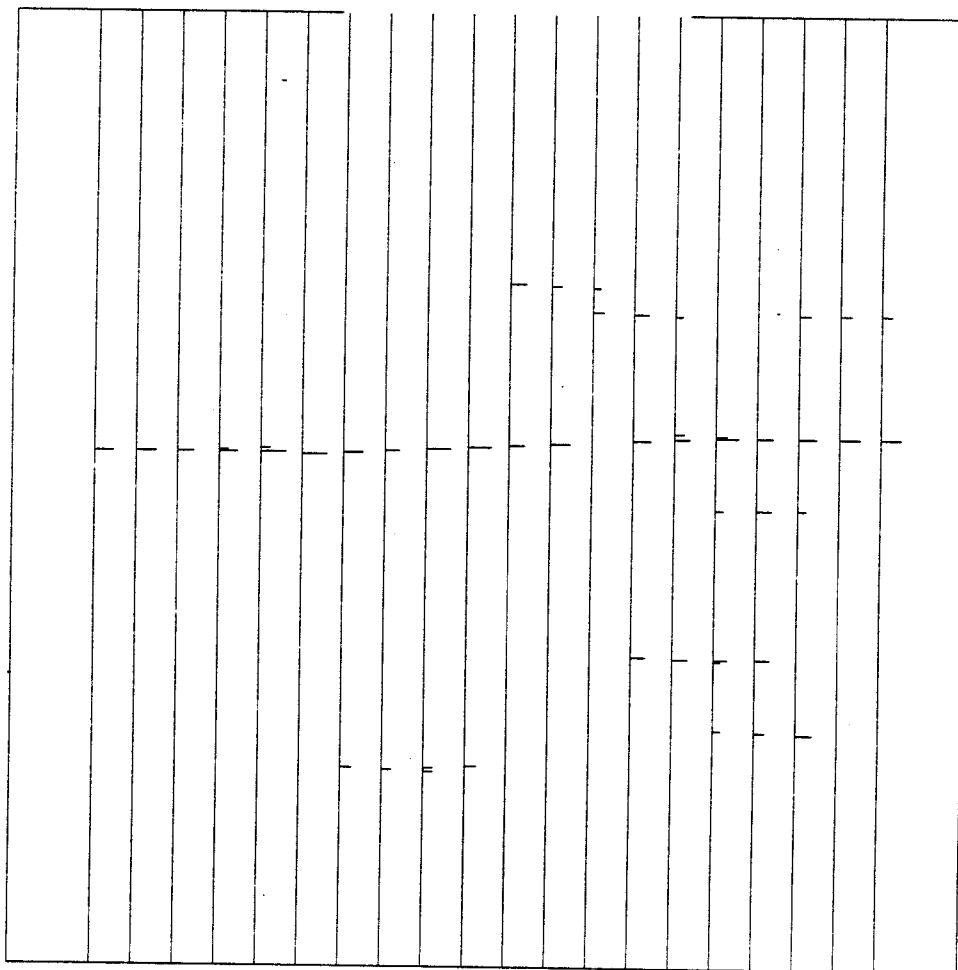


Figure 7. Result of LRT and  $\chi^2$ - Test Spatial Decision Rule (3 patterns, 3 testing points per pattern).