SEISMIC HYPERBOLIC PATTERN DETECTION AND VELOCITY ANALYSIS BY SIMULATED ANNEALING

Kuo-Chen Huang[1], Kou-Yuan Huang[2], Luke K. Wang[1], Ying-Liang Chou[2], Yueh-Hsun Hsieh[2], and Shan-Chih Hsieh[1]
[1]Department of Electrical Engineering, National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan
[2]Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan
E-mail: kyhuang@cs.nctu.edu.tw

1. INTRODUCTION

There are hyperbolic patterns on seismic common-depth-point (CDP) gathers [1]-[4]. In 1985, Huang et al. had applied Hough transform (HT) to detect hyperbolic pattern of reflection wave [5]. However, the determination of the parameters of the pattern in the parameter space was not easy and memory requirement was also a problem.

In 2002, Hough transform neural network (HTNN) was proposed to detect lines, circles, and ellipses, but it did not detect hyperbolas [6]. In 2006, Huang et al. adopted HTNN to detect lines of direct wave and hyperbola of reflection wave in a one-shot seismogram [7]. But the gradient descent method in HTNN had local minimum problem.

In 1983, Kirkpatrick et al. proposed simulated annealing (SA) [8]. It is a global optimization algorithm. The key of the algorithm to reach the global minimum is in conditionally accepting higher-energy states by Metropolis criterion [9].

Here, adopting the advantage of SA, we propose seismic pattern detection system to the parameter detection of hyperbolic patterns on CDP gather. The parameters are used to calculate the root-mean-squared velocity V_{rms}. The V_{rms} can be used to the normal-moveout correction (NMO) and stacking. Each CDP gather becomes a trace. We collect the total traces to restore the image of the subsurface. This method is different from the conventional velocity spectral analysis.

2. METHOD: SEISMIC PATTERN DETECTION SYSTEM

We propose the detection system in Fig. 1. First, we preprocess the input seismic data by envelope processing and threshold processing. It takes the N data as the input from the preprocessed image, then through the SA parameter detection system to detect a set of parameter vectors of K patterns. After convergence, patterns are recovered from the detected parameter vectors.

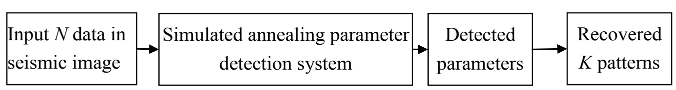

Fig. 1. Block diagram of the SA detection.

We use a general equation based on the translation and rotation of the standard type of hyperbola.

$$a[(x-m_x)\cos\theta+(y-m_y)\sin\theta]^2+b[-(x-m_x)\sin\theta+(y-m_y)\cos\theta]^2=f \tag{1}$$

In vector form, a parameter vector $\mathbf{p} = [m_x, m_y, a, b, \theta, f]^T$ represents a pattern. When ($a > 0$, $b < 0$, and $f \neq 0$) or ($a < 0$, $b > 0$, and $f \neq 0$) the graph is a hyperbola.

We define the distance from a point $\mathbf{x}_i = [x_i, y_i]^T$ to the kth pattern as

$$d_k(\mathbf{x}_i) = |\, a_k[(x_i-m_{k,x})\cos\theta_k+(y_i-m_{k,y})\sin\theta_k]^2+b_k[-(x_i-m_{k,x})\sin\theta_k+(y_i-m_{k,y})\cos\theta_k]^2-f_k\,| \tag{2}$$

We define distance of the ith point $\mathbf{x}_i$ to the total number of K patterns as

$$E_i(\mathbf{x}_i) = \min\left(d_1(\mathbf{x}_i), d_2(\mathbf{x}_i), \ldots, d_k(\mathbf{x}_i), \ldots, d_K(\mathbf{x}_i)\right) \tag{3}$$

We define the average distance of N input points to K patterns as the error or energy of the system,

$$E = \frac{1}{N}\sum_{i=1}^{N} E_i(\mathbf{x}_i) \tag{4}$$

Then we use the SA to adjust the parameters: center (m_x, m_y), the shape parameters a and b, and then the rotation angle θ, followed by the size f, sequentially step by step. After convergence, we recover the detected hyperbolic patterns.

3. FROM PARAMETER DETERMINATIOIN BY SIMULATED ANNEALING TO VELOCITY ANALYSIS

In experiment, we apply the seismic pattern detection system to CDP gather data for hyperbolic pattern detection and velocity analysis. First, we build a 5 layer geologic model; each layer has different density and interval velocity. Then we obtain the CDP gather from 40 shot records. Second, we detect the parameters of hyperbolic pattern on the CDP gather, as shown in Fig. 2. The detected parameters are used to calculate the root-mean-squared velocity V_{rms}. Finally, we use the V_{rms} to do the NMO correction and stacking. After NMO and stacking, each CDP gather becomes a trace. We collect the total traces to restore the image of the subsurface, as shown in Fig. 3(a). Figure 3(b) is the restored image of the subsurface by the conventional VSPEC method.

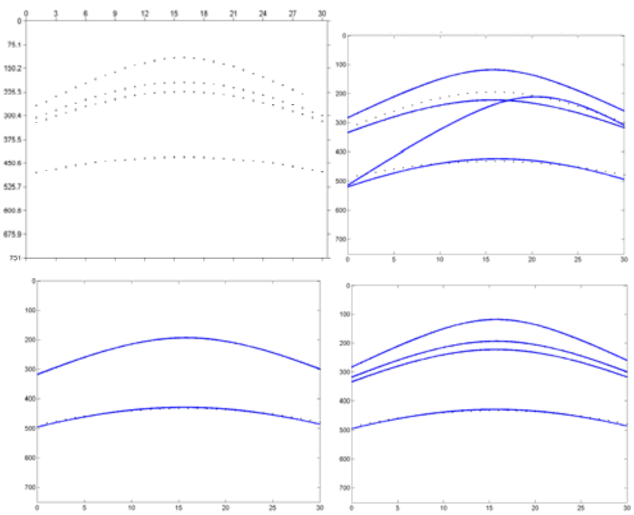

Fig. 2. (a) CDP gather after processing. (b) First detection result. (c) Second detection result on remaining data. (d) Final result by detection system.

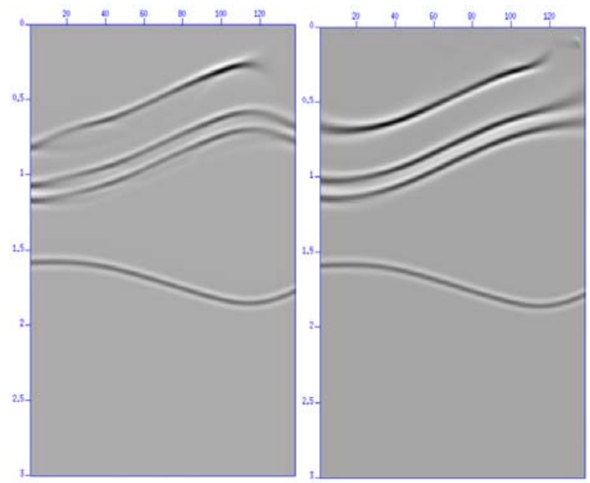

Fig. 3. (a) The restored image of the subsurface by detected system. (b) The restored image of the subsurface by VSPEC.

3. CONCLUSIONS

We use the simulated annealing for the detection of hyperbolas. The simulated annealing has the capability of searching a set of parameter vectors with global minimal error. The general equation of hyperbolas in detection is from translation and rotation of standard equation. We use the SA to adjust the hyperbolic parameters: center (m_x, m_y), the shape parameters a and b, and then the rotation angle θ, followed by the size f, sequentially step by step. After convergence, we recover the detected hyperbolic patterns.

In seismic experiment, we use seismic pattern detection system to detect the parameters of hyperbolic patterns on CDP gather. The parameters are used to calculate the root-mean-squared velocity V_{rms}. The V_{rms} can be used to the NMO correction and stacking. The restored image is as good as the result of the conventional velocity spectral analysis. And the difference is that we do not need to do the velocity picking in the conventional velocity spectral analysis.

4. ACKNOWLEDGMENT

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