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Automatic picking algorithm for stacking velocity based on Bayesian estimation

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ABSTRACT
The stacking velocity is an important parameter for velocity analysis and migration imaging. How to find the optimal stacking velocity from a large amount of signal data is a key issue in the interpretation of seismic data. In this paper, Bayesian estimation has been used for the automatic pick-up of optimal stacking velocity. A set of signal values are determined by looking forward for the maximum probability "energy sequence" of the joint probability distribution of the observation sequence and the state sequence, as well as the backward cumulative calculation of the joint probability distribution maximum path. This set of signal values is used to calculate the optimal stacking speed. Experiment results obtained show that the proposed algorithm work well with the complex terrain signal data, and meets the accuracy requirements in actual engineering. The algorithm can quickly provide a reasonable and effective speed model for subsequent data analysis.

***Keywords* -**Stacking velocity, Velocity spectrum, Automatic picking, Bayesian estimation

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I. INTRODUCTION

The propagation velocity of seismic waves in underground rock media is an important parameter for processing and interpreting geophysical data. Using velocity spectrum to pick up the best superimposed velocity value is one of the core issues in processing seismic data [1]. In the face of hundreds of millions of data to be processed, there is a growing need for automatic stacking velocity picking algorithm to replace the manual selection.

Automatic picking is often achieved through a combination of objective function and optimization methods. Liu proposed a new method of pre-stack velocity analysis using weighted similarity [2], Xu reconstructed the superposition velocity analysis problem as a sparse inverse problem, and gave a new matching pursuit (MP) algorithm to achieve automatic picking speed value [3], Reiche proposed a normalized variational method based on non-rigid image matching technology to replace the traditional stacking method [4], Leite proposed a non-linear method for automatic speed pickup in the likelihood domain [5]. These methods are suitable for processing channel data with uniformly distributed sequences and high signal-to-noise ratio, but they are susceptible to interference from noise and terrain signals. With the widespread application of machine learning, various deep learning methods based on neural networks have also been applied to the automatic pick-up of speed spectrum parameters [6] [7], but due to the large amount of calculation, they have not been well applied in practice.

For channel data collected under complex terrain conditions, probability-based methods can effectively solve the problem of distortion of some channel data due to noise and terrain factors, such as Monte Carlo random disturbance method [8], Viterbi algorithm [9], etc. Bayesian method [10] adopts the idea of maximum posterior probability, takes the observation sequence and state transition sequence as the prior probability and conditional probability, and simulates the channel distribution sequence conforming to a large amount of actual data through the joint distribution of the two, which can effectively improve the calculation accuracy of the objective function [11].

In this paper, Bayesian estimation is introduced into the picking calculation of the optimal stacking velocity value. The stacking velocity value in the velocity spectrum can be automatically picked up by calculating the maximum "energy sequence" in the forward direction and the maximum posterior probability through the backward cumulative calculation. The experimental results show that the optimal stacking velocity value calculated by the method in this paper is close to the true value, and the accuracy meets the actual requirements.

II. OBJECTIVE FUNCTION

In velocity signal processing, the velocity spectrum is often used to obtain stacking velocity, as shown in Figure 1[1]. $X = (X_1, X_2, \dots, X_N)$ represents the collected N channel data, t_0 is the two-way reflection time with zero shot spacing, Δt is the dynamic correction amount (normal time difference), and H is the best time delay for dynamic correction In the curve, $\tilde{V}$ is the stacking velocity, and $\bar{A}$ is the average amplitude energy of N channels.

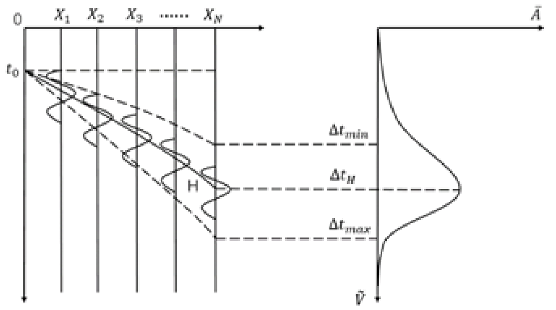

Fig 1 Average amplitude energy of velocity spectrum.

In order to obtain the most suitable time delay curve, according to the principle of seismic wave analysis, the minimum energy error criterion can be used here:

$$E = argmin\left[\sum_{j=0}^{M}\sum_{i}^{N} X_{i,j+r_i}^2 - \frac{1}{N}\sum_{j=0}^{M}\left(\sum_{i}^{N} X_{i,j+r_i}\right)^2\right] \quad (1)$$

In equation (1), $X_i (i = 1,2,3, \dots, N)$ is N channel data, j=(0,1,2,...,M) is the sampling point number in each channel, and t_{xi} is the corresponding X_i Two-way reflection time, δt is the sampling interval, $r_i = t_{x_i}/\delta t$ is the delay amount.

When there is an interference background, the minimum value of equation (1) is often not obvious, so the problem of minimum value can be transformed into finding the maximum value of similar coefficients for discrimination by using an equivalent method [1]:

$$R = argmax\frac{\sum_{j=0}^{M}\left(\sum_{i}^{N} X_{i,j+r_i}\right)^2}{N\sum_{j=0}^{M}\sum_{i}^{N} X_{i,j+r_i}^2} \quad (2)$$

$\sum_{j=0}^{M}\left(\sum_{i}^{N} X_{i,j+r_i}\right)^2$ is the sum of the energy sum of the squared amplitudes of the N recordings, and the denominator term $\sum_{j=0}^{M}\sum_{i}^{N} X_{i,j+r_i}^2$ is the sum of the superimposed energy of the squared amplitudes of the N tracks. The value of the similarity coefficient R is between 0 and 1. The closer to 1, the smaller the energy error.

According to the reflected wave travel time formula, the delay amount r_i is a function of the propagation time t_0 and the stacking velocity $\tilde{V}$:

$$r_i = t_{x_i}/\delta t = \frac{1}{\delta t}\sqrt{t_0^2 + \frac{S_i^2}{(\tilde{V})^2}} = r_i(t_0, \tilde{V}) \quad (3)$$

In this way, the minimum energy error problem (1) is transformed into selecting an appropriate time t_0 and stacking velocity $\tilde{V}$, which makes the similarity coefficient R reaches the maximum value.

III. BAYESIAN METHOD

Bayesian estimation uses the joint distribution probability of the observation sequence of known data and the hidden state sequence, to calculate the observation sequence with the largest posterior probability (the expected risk is the smallest) as the optimal solution instead of seeking the derivative (gradient-based optimization) to process optimization, which adapts to the actual situation of various complex distributions better.

Using Bayesian estimation to solve the problem can be divided into two steps: (1) the cumulative calculation of the maximum "energy sequence" of the velocity spectrum in the forward direction; (2) the backward tracking of the posterior probability to find the best velocity value.

In order to show the method in this article, a 7x7 simulation numerical matrix (example) is used for illustration as shown in Figure 2.

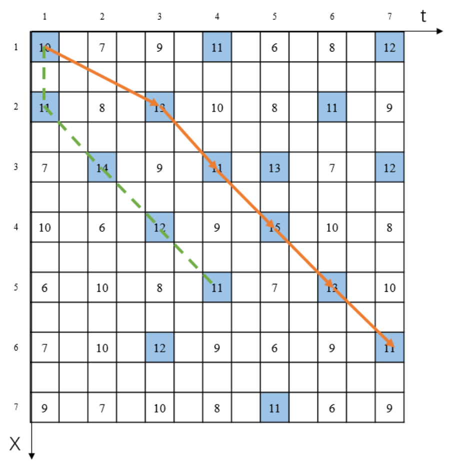

Fig 2 Analog numerical matrix.

In Figure 2, the abscissa t represents time, and the ordinate X represents each channel. For the convenience of calculation, the value in the matrix is obtained by multiplying the actual channel amplitude value by 100 and rounding its absolute value. The optimization of the analog matrix is a path from (1,1) to (6,7), and the optimization direction is Including the corresponding point and the point at the same time in the next line and the two points on the right.

3.1 Forward search to determine the maximum "energy sequence"

According to N order Markov process, the state q_t at time t depends only on the state at time t-1:

$$P(q_t|q_1, q_2, \dots, q_{t-1}) = P(q_t|q_{t-1}) \tag{4}$$

$P(q_1)$ is the initial observation sequence probability, $P(q_t|q_{t-1})$ is the observation sequence conditional distribution probability. This can greatly reduce the dimensionality of the problem.

According to Bayesian theory, the relationship between the channel data observation sequence q_t and the state sequence a_t can be expressed as:

$$P(a_t, q_t) = P(q_1)\prod_{t=1}^{T-1} P(q_{t+1}|q_t)\prod_{t=1}^{T} P(a_t|q_t) \tag{5}$$

$P(a_t|q_t)$ is the probability of state a_t when the observation value is q_t.

The most likely observation sequence q_t^* can be obtained by using MAP (Maximum a posteriori estimation):

$$q_t^* = argmax P_{q_t}(a_t, q_t) \tag{6}$$

q_t^* is the maximum value of the joint probability distribution $P(a_t, q_t)$. The implicit state chain corresponding to q_t^* is the "energy sequence" of the transfer probability of the best stacking velocity value.

In the calculation example, the two-dimensional matrix is subjected to a positive numerical simulation calculation along the direction where X increases as well as the direction where t increases, searching for the maximum velocity spectrum energy cluster, and forwarding the probability calculation as shown in Figure 3:

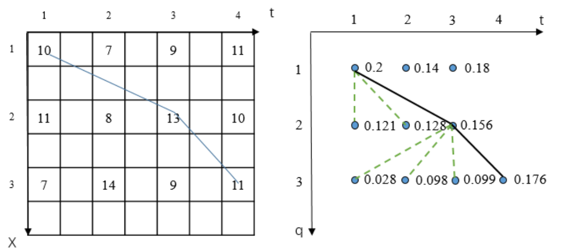

Fig 3 Forward search for the largest "energy sequence"

3.2 Reverse the tracking of the maximum posterior probability

Firstly, define:

$$L(q_t, t) = max_{q_{t-1}} P(a_t, q_{t-1}) \tag{7}$$

$L(q_t, t)$ is the maximum value of the joint probability distribution $P(a_t, q_{t-1})$, which is actually the maximum value of the state sequence $P(a_t)$, but it depends on the observation sequence distribution probability $P(q_{t-1})$. Then, it is calculated recursively by the following equation (8):

$$L(q_t, t) = P(a_t|q_t) max_{q_{t-1}}[P(a_t, q_{t-1}) L(q_{t-1}, t-1)] \tag{8}$$

Regarding the velocity spectrum as an observation sequence q_t, the state sequence a_t is used to record the transfer variables of the "probability path", the accumulation process of the largest "energy cluster" of the spectrum can be expressed as:

$$\begin{cases} \bar{X}(x_i, y_j) = \bar{X}_{max}(x_{i,t}, y_{j-1}) + X(x_i, y_j) \\ L(x_i, y_j) = x_i(y_{j-1}) \,|_t \end{cases} \tag{9}$$

$\bar{X}(x_i, y_j)$ is the result of accumulation under constraint conditions, and $L(x_i, y_j)$ records this accumulation process.

When the above accumulation reaches $y_j = y_{N-1}$, the maximum value $\bar{X}(x_i, y_j)$ can be searched. At the same time, the shortest path is searched backward recursively and the required stacking velocity value $v(y_j)$ is calculated:

$$\begin{cases} x_{ipick}|y_{j-1} = L(x_{ipick}|y_j, y_{j-1}) \\ v(y_j) = x_{ipick}|y_j \end{cases} \tag{10}$$

In the calculation example, reverse the cumulative calculation of the joint probability of the state sequence and the observation sequence as shown in Figure 4. The cumulative probability of path 1 is greater than the cumulative probability of path 2 (0.956>0.713), and the best choice is path 1.

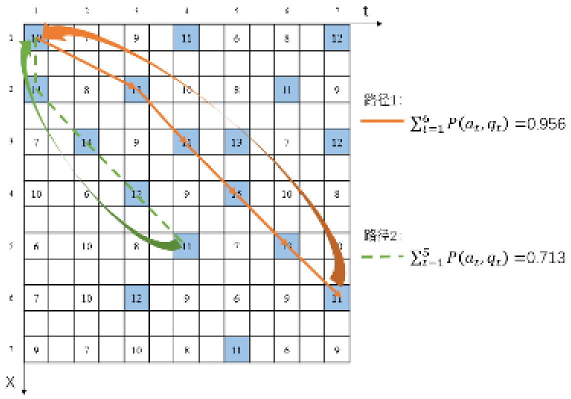

Fig 4 The tracking of the maximum posterior probability

IV. EXPERIMENTS

In this paper, the tunnel geological advanced prediction problem in the geophysical prospecting is used to verify the effectiveness of the algorithm. The advanced forecast of tunnel geology is the forecast of the surrounding rock around the tunnel head. The important link is to select the point with the largest average energy amplitude in the speed scan coordinate system and its delay curve of the event axis in the channel diagram as shown in Figure 5.

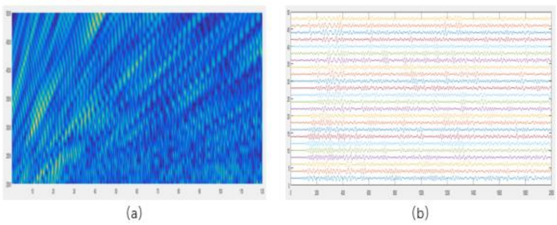

Fig 5 The speed scan energy map and channel map

MODEL 1

A four-layer layered model is established based on the general geological conditions of the tunnel. The face of the tunnel is located 30m in front of the geophone. The length of the tunnel to be excavated is 120m, the width is 12m, and the height is 6m. The results and errors calculated by the algorithm in this paper are shown in Table 1. Compared with the theoretical velocity and interface, the error is very small and close to the theoretical value; the stacking velocity value obtained by the algorithm in this paper is located in the optimal energy band, its dynamic correction curve passes through the peaks of each channel as shown in Figure 6.

Table 1 Comparison table of theoretical and calculated values

level	1	2	3	4
theoretical velocity(m/s)	3020	3185	3575	3440
Computing velocity(m/s)	3000	3200	3500	3500
error(%)	0.66	0.47	2.10	1.74
theoretical interface(m)	37.4	65.0	107.2	135.6
Computing interface(m)	37.2	65.8	106.6	139.0
error(%)	0.53	1.23	0.56	2.51

MODEL 2

Channel data during tunnel construction in Caoba area (including noise and interference). The tunnel face is located 35m in front of the geophone.

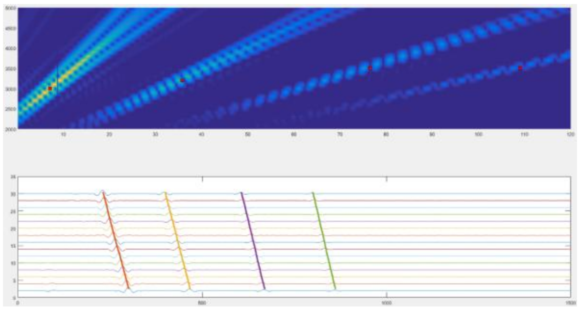

Fig 6 The superimposed velocity value and channel curve obtained by the algorithm

The length of the tunnel to be excavated is 120m, width 12m, and height 7m. The calculation results and errors of this algorithm are shown in Table 2. The velocity and interface errors in the first three layers are very small and close to the theoretical values. The errors in the fourth layer is greatly affected by noise and interference signals, due to the long spatial distance from the detector; The stacking velocity value of is located inside the optimal energy band, its curve passes through the peak or trough of each channel (both are points with larger amplitude energy) as shown in Figure 7.

Table 2 Comparison table of the measured and calculated values

level	1	2	3	4
measured velocity(m/s)	2475	2600	2900	2675
Computing velocity(m/s)	2500	2600	2900	2600
error(%)	1.01	0.00	0.00	2.80
measured interface(m)	42.0	62.0	102.0	123.0
Computing	42.4	62.2	101.8	116.8

interface(m)				
error(%)	0.95	0.32	0.20	5.04

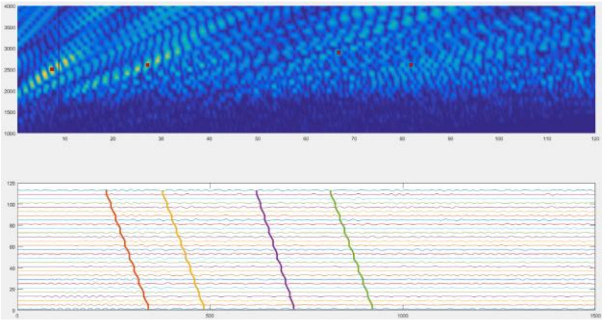

Fig 7 Actual excavation velocity spectrum and energy spectrum in caoba area

V. CONCLUSION

In this paper, an automatic picking algorithm for optimal stacking velocity based on Bayesian estimation is proposed, and good results have been obtained in the theory and measured model of the tunnel advanced prediction problem. By calculating the maximum posterior probability of the joint distribution of the forward and reverse sequence to determine the optimization direction and path, the goal of automatically picking the best superimposed velocity value more accurately is achieved. It is of positive significance to reduce possible economic and exploration losses (due to the high calculation cost and part of the speed information may be picked up in the speed analysis), as well as improve the production efficiency in the geophysical prospecting.

However, the Bayesian method is limited by the velocity versatility of the energy map and the low signal-to-noise ratio of the actual data because it is dependent on the initial model (the quality of the initial observation sequence directly affects the picking accuracy). The relevant research needs to be discussed in depth.

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