# Automatic migration velocity estimation for pre-stack time migration

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Automatic migration velocity estimation for pre-stack time migration

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Running Head: Automatic MVA for PSTM

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ABSTRACT

Migration velocity analysis is a labor-intensive part of the iterative pre-stack time migration process. We have proposed a velocity estimation scheme to improve the efficiency of the velocity analysis process using an automatic approach. The proposed scheme is the numerical implementation of the conventional velocity analysis process based on the residual moveout analysis. The key aspect of this scheme is the automatic event picking in the common reflection point gathers, which is implemented by semblance scanning trace by trace. With the picked travel time curves, we estimate the velocities at discrete grids in the velocity model using the least-squares method, and build the final root-mean-square velocity model by spatial interpolation. The main advantage of the proposed method is that it can generate an appropriate root-mean-square velocity model for pre-stack time migration in just a few iterations without manual manipulations. In addition, using the fitting curves of the picked events in a range of offsets to estimate the velocity model, which is fitting to a normal moveout correction, can prevent the proposed scheme from local minima issue. The Sigsbee2B model and a field data set are used to verify the feasibility of the proposed scheme. High-quality velocity model and imaging results are obtained. Comparing to the computational cost to generate the common reflection point gathers, the cost of the proposed scheme can be neglected, and the quality of the initial velocity is not critical.

INTRODUCTION

The accuracy of migration velocity model determines the imaging quality of pre-stack time migration (PSTM). Root-mean-square (RMS) velocity is generally used
as the migration velocity for PSTM. For complex structures, the pursuit of an
acceptable RMS velocity model is usually performed by several iterations of migration
and human interactive velocity analysis. In order to accomplish this loop process, a
criterion should be created to judge whether the used migration velocity model is
optimal or not, and an effective method should be applied to update the velocity model
when it is necessary. Intuitively, if the current velocity model is good enough, each
subsurface reflector from different seismic data will converge to the same position.
Then, the events in the common reflection point (CRP) gathers will be aligned
horizontally. Otherwise, the events in the CRP gathers will be displayed as migration
smiles or frowns.

One category of the migration velocity analysis (MVA) methods is based on the
analysis of the migrated CRP gathers using an initial velocity model. Al-Yahya (1989)
describes the MVA scheme based on the residual moveout (RMO) curvature analysis
of the CRP gathers that are migrated using an incorrect velocity model. Because of its
conceptual clarity and simplicity, this scheme has already been one of the most
frequently used schemes for MVA. Based on Al-Yahya's (1989) moveout formula for
a flat reflector, many algorithms have been proposed (Deregowski, 1990; Liu and
Bleistein, 1995; Liu, 1997; Fei and McMechan, 2006). For PSTM, the RMS velocity
model is usually updated by applying an inverse normal moveout (NMO) correction to
the migrated CRP gathers and implementing a conventional NMO-based velocity
to dipping reflectors by adding a parameter to achieve higher accuracy. Zhang et al.
(2012) extends PSTM to handle rugged topography by adding a new velocity parameter.

Another category of MVA methods is devised based on the analysis of images that are migrated using a series of migration velocities. Fomel (1994), Hubral et al. (1996), and Schleicher et al. (1997) describe the process of transforming time migrated images according to the variations in migration velocities. Goldin (1994) develops a theory of image continuation. Fomel (2003a, 2003b) further discusses the kinematics and dynamics of image continuation or velocity continuation thoroughly, and extends the theory to the pre-stack domain. Based on velocity continuation, Coimbra et al. (2013a) describe the process of velocity estimation for depth migration using remigration trajectories in the post-stack domain. Coimbra et al. (2013b) further develop this work and apply it to pre-stack case. Santos et al. (2015) extend the remigration trajectory MVA method to make it suitable for PSTM. One of the weaknesses of this method is that it also requires time-consuming iterative event-picking (Santos et al., 2015).

As the high-density seismic data acquisition is generally adopted in the seismic industry, processing the massive volume of data becomes a heavy burden for seismic imaging. In order to reduce the human interactions in seismic imaging, velocity-independent imaging methods and automatic velocity estimation methods have been proposed. Common-reflection-surface (CRS) stacking (Müller, 1998; Mann et al., 1999; Jäger et al., 2001; Garabito et al., 2012), multifocusing (Gelchinsky et al., 1999a, 1999b), and path-integral imaging (Keydar, 2004; Landa, 2004, 2013; Landa et
al., 2006) are three representative velocity-independent imaging techniques. The CRS stacking relies on a hyperbolic travel time surface (Jäger et al., 2001), and the multifocusing method uses double-square-root operator to describe the travel time surface (Gelchinsky et al., 1999a). Both the CRS stacking and multifocusing methods produce zero-offset seismic section by summing the amplitudes of seismic reflection events with stacking operators corresponding to three wavefront kinematic attributes: the emergence angle, the radius of the normal wave, and the radius of the normal-incidence-point wave. These attributes are usually estimated with minimal assumptions about the subsurface velocity, which may be trapped in a local minimum (Garabito et al., 2012). The path-integral imaging produces the accurate subsurface image by summing a set of possible images using different velocity models in a weighted manner. In this approach, the appropriate weighting function plays an important role in emphasizing the contributions from the optimal travel time curves and suppressing the contributions from the unrealistic curves (Landa et al., 2006). Schleicher and Costa (2009) proposed a method to extract the migration velocity model by double path-integral imaging. A proper implementation of these approaches is computational expensive. Based on nonrigid image-matching, Reiche and Berkels (2018) develop an automatic stacking technique. Image-matching is a nonphysical method to flatten the seismic gathers. With the offset-dependent traveltime information as a by-product of image matching, stacking velocities can be calculated using the conventional hyperbolic traveltime equation.

Differential semblance optimization (DSO) method (Symes and Carazzone, 1991;
Symes, 2008; Yang et al., 2013) is one strategy of image-domain wavefield
tomography. This method defines a cost function to evaluate and update the migration
velocity model. The DSO cost function has better global convexity properties than the
least-square function (Symes and Carazzone, 1991; Mulder and Kroode, 2002).
However, the gradient is severely contaminated by artifacts (Sun and Alkhalifah,
2018). Recent developments (Hou and Symes, 2015, 2017; Chauris and Cocher, 2017)
demonstrate that such artifacts can be suppressed by inversion for the reflectivity
rather than migration. This reveals that the DSO procedure is sensitive to the
amplitudes of the image gathers, requiring "true amplitude" imaging (Sun and
Alkhalifah, 2018).

Extending the work of Ottolini (1983) , Fomel (2007) shows that it is possible to
commit PSTM using local event slopes alone without estimating seismic velocities
or any other attributes. Local slant stack (Ottolini, 1983), Hilbert transform (Cooke et
al., 2009; Wang et al., 2015) and plane-wave destruction (Fomel, 2002; Schleicher et
al., 2009) can be used to extract the local event slopes. Zhang and Lu (2016) propose
an automatic time-domain MVA method based on clustering local attributes that have
been mapped from local event slopes. The accuracy of the estimated local event slopes
is sensitive to noise, and influences the quality of the final velocity model and the
imaging result (Zhang and Lu, 2016). Sakamori and Biloti (2018) extend the RMO
analysis by deriving an accurate description of RMO and estimate the parameters
 corresponding to the dip and the ratio between the migration velocity and the true
medium velocity in supergathers by using a derivative-free optimization method. The
application of supergathers improves the quality of the estimated parameters and enhances the computational efficiency.

In this paper, we propose an automatic MVA scheme for PSTM. This scheme is the numerical implementation of the conventional time domain MVA based on the RMO analysis. It mainly involves two steps: automatic event picking and velocity model building. The automatic event picking is performed by semblance scanning trace by trace. With the fitting curves of the picked traveltime curves, we calculate their corresponding zero-offset travel-times and velocities by solving nonlinear equations. Performing PSTM on sparse imaging grids leads to high computational efficiency. And calculating the velocity model with the fitting curves fitting to a NMO correction prevents the proposed scheme from local minima issue. We apply the proposed scheme to the Sigsbee2B and field data sets, and obtain good velocity models and final migration results.

METHODOLOGY

In the PSTM loop schedule, the popular procedure to build the RMS velocity model using the CRP gathers is the following (Biondi, 2006): First, inverse NMO correction is applied to the CRP gathers with the migration velocity model. Second, conventional velocity spectra are computed from the gathers after inverse NMO correction. Third, the conventional NMO-based velocity analysis is applied to obtain the updated RMS velocity model. In this procedure, the NMO-based velocity analysis requires a lot of human interaction, and the experiences of the processors determine the accuracy of the built velocity model.
In order to avoid the human interaction in the RMS velocity estimation, we adopt an automatic method to pick the traveltime curves of the reflection events in the CRP gathers, and calculate the RMS velocity model by solving nonlinear equations. The proposed approach mainly includes the following steps:

1) Applying PSTM to the seismic data to generate CRP gathers using an initial velocity model.

2) Automatic picking the traveltime curves of the reflection events in the CRP gathers, and calculating their fitting curves using the least-squares fitting method.

3) Calculating the zero-offset travel times and RMS velocities corresponding to the picked curves to build the updated velocity model.

For complex structures, the iterative process is needed. In this loop process, the key aspect is to pick the events automatically and calculate the zero-offset traveltimes and RMS velocities corresponding to the picked curves.

**Method to calculate the zero-offset travel time and RMS velocity**

In the conventional PSTM loop schedule, the inverse NMO correction and NMO-based velocity analysis are both based on hyperbolic assumption. For a single horizontal layer with constant velocity, the reflection traveltime equation as a function of offset is

\[ t^2 = t_0^2 + \frac{h^2}{v^2}, \]

(1)

where \( h \) is the source-receiver offset, \( t_0 \) is the two-way zero-offset traveltime, and \( v \) is the velocity of the medium above the interface.
For one selected event in a CRP gather, we represent its position at \( i \)-th trace as \((h_i, \tau_i)\), where \( h_i \) and \( \tau_i \) are its corresponding offset and the pseudo-depth denoted by two-way traveltime, respectively. Applying an inverse NMO correction to this CRP gather with the migration velocity model \( v_1 \), the point \((h_i, \tau_i)\) in the original CRP gather will be transformed to the new position \((h_i, t_i)\) along the vertical direction.

The new travel time \( t_i \) can be expressed by

\[
t_i = \sqrt{\tau_i^2 + \frac{h_i^2}{v_1^2(\tau_i)}}, \quad i = 0, 1, \ldots, m - 1,
\]  

(2)

where \( v_1(\tau_i) \) is the velocity at the pseudo-depth denoted by traveltime \( \tau_i \), and \( m \) is the number of the traces in the CRP gather.

Despite of the process of MVA, an NMO correction using the final velocity model \( v_2 \) can flatten the event to its zero-offset traveltime \( t_0 \). According to equation 1, this NMO correction process can be written as

\[
t_0^2 = t_i^2 - \frac{h_i^2}{v_2^2(t_0)}.
\]  

(3)

Substituting equation 2 into equation 3, both process of the inverse NMO correction with the initial migration velocity \( v_1 \) and the NMO correction with the updated velocity \( v_2 \) can be expressed in an equation as

\[
f_i(t_0, v_2(t_0)) = t_0^2 - t_i^2 - \frac{h_i^2}{v_1^2(\tau_i)} + \frac{h_i^2}{v_2^2(t_0)}, \quad i = 0, 1, \ldots, m - 1.
\]  

(4)

For a set of \( m \) nonlinear equations 4, there are two unknown variates \( t_0 \) and \( v_2(t_0) \). We represent their optimal solutions as \( t_0^* \) and \( v_2^*(t_0^*) \), which can be determined by solving an optimization problem to minimize the L2 norm

\[
\min \sum_{i=0}^{m-1} [f_i(t_0, v_2(t_0))]^2.
\]  

(5)

In this paper, we use the least-squares method (Gill and Murray, 1978) to solve
this problem. Performing the Taylor Series expansion on $f_i(t_0, v_2(t_0))$ around initial values $t_0^0$ and $v_2^0(t_0^0)$, and neglecting the higher order terms, the nonlinear equations are transformed to linear equations

$$f_i(t_0, v_2(t_0)) = f_i(t_0^0, v_2^0(t_0^0)) + (t_0 - t_0^0) \frac{\partial}{\partial t_0} f_i(t_0^0, v_2^0(t_0^0)) + (v_2(t_0) - v_2(t_0^0)) = 0,$$

$i = 0, 1, \ldots, m - 1.$ \hfill (6)

The Jacobian matrix of the linear equations is

$$J(t_0, v_2(t_0)) = \begin{bmatrix}
\frac{\partial f_0}{\partial t_0} & \frac{\partial f_0}{\partial v_2(t_0)} \\
\frac{\partial f_1}{\partial t_0} & \frac{\partial f_1}{\partial v_2(t_0)} \\
\vdots & \vdots \\
\frac{\partial f_{m-1}}{\partial t_0} & \frac{\partial f_{m-1}}{\partial v_2(t_0)}
\end{bmatrix} = 2 \times \begin{bmatrix}
t_0 & -v_2^0 \left( t_0^0 \right) \\
t_0 & -v_2^1 \left( t_0^0 \right) \\
\vdots & \vdots \\
t_0 & -v_2^{m-1} \left( t_0^0 \right)
\end{bmatrix}. \hfill (7)

Expressing the least-squares solutions of the linear equations at the $j$th iteration as vector $\mathbf{x}' = \left( t_0', v_2'(t_0') \right)$, equations 6 can be written as

$$f(\mathbf{x}') + J(\mathbf{x}') (\mathbf{x} - \mathbf{x}') = 0. \hfill (8)$$

For this over-determined linear equations, their least-squares solutions are

$$\mathbf{x}' = \mathbf{x} - J^{-1}(\mathbf{x}') f(\mathbf{x}'). \hfill (9)$$

where $J^{-1}$ is the generalized inverse of the Jacobian matrix. The optimization solution $\mathbf{x}^* = \left( t_0^*, v_2^*(t_0^*) \right)$ can be calculated in an iterative manner by

$$\mathbf{x}^{k+1} = \mathbf{x}^k - J^{-1}(\mathbf{x}^k) f(\mathbf{x}^k). \hfill (10)$$

Assigning each calculated velocity value $v_2(t_0)$ to its corresponding position $(x, y, t_0)$, where $(x, y)$ is the lateral position of the CRP, it recovers a sparse velocity model. Then, spatial interpolating method is used to generate the updated
velocity model.

**Automatic event picking**

In order to get the correct zero-offset traveltime and RMS velocities using the described method, the travel time curves must be accurate. In the seismic interpretation, a large number of automatic horizon tracking methods have been developed (Woodham et al., 1995; Glinsky et al., 2001; Luo and Hale, 2013; Jin et al., 2017). In this paper, we calculate the time lag between two consecutive traces by semblance scanning, and form the travel time curves with the time lags. The automatic event picking scheme mainly involves two steps: determining the position of the selected events in the first trace and calculating the time lags trace by trace. For the seismic data acquired over complex structures or with low signal-to-noise ratio (SNR), using supergathers obtained by laterally stacking the adjacent CRP gathers in a small range can improve the SNR of the CRP gathers and the quality of the updated velocity model.

For the first trace, we define the energy at each time sample as

\[ E(i) = D^2(i), \quad i = 0, 1, \ldots, nt - 1, \]

where \( D \) denotes the seismic data, \( nt \) is the number of samples.

We apply a sliding time window to the energy trace and pick the times corresponding to the maximum amplitude in the sliding windows. The picked times correspond to the positions of the selected events on the first trace. For one picked time \( \tau(0) \), we extract a piece of data from the original trace with this time as the center of a time window (Figure 1).
The discrete form of the cross correlation function between two consecutive traces is

\[ C_j(n,k) = \sum_{i=-L_t/2}^{L_t/2} D_j(n+i)D_{j+1}(n+k+i), \]  

where \( n \) is the sample number of the picked time in the \( j \)th trace, \( L_t \) is the length of the time window, \( k \) is the time difference between the time windows applied to the consecutive traces.

If \( k \) is corresponding to the correct time difference, the waveforms of the extracted signals from two consecutive traces have maximum similarity (Figure 1), and the value of \( C_j(n,k) \) reaches its peak. We denote the travel time difference between the \( i \)th trace and \((i+1)\)th trace by \( \Delta \tau_i \). Then, the travel time function of the selected event is

\[ \tau(j) = \tau(0) + \sum_{i=0}^{j-1} \Delta \tau_i, \quad j = 1, 2, \ldots, m - 1. \]  

Figure 2b shows the picked curves for a CRP gather shown in Figure 2a. Due to the presence of migration noises or crossing events, there are always errors with \( \Delta \tau_i \), which make the travel time function inaccurate. In this paper, we use least-squares curve fitting method (Hamming, 1962) to get the smoothed curve

\[ T(h) = \sum_{i=0}^{K-1} a_i(h - \bar{h})^i, \]  

where \( a_i \) is the coefficient of the fitting equation, \( \bar{h} = \frac{1}{m-1} \sum_{i=1}^{m-1} h_i \), and \( K \) is the order of the polynomial.

Figure 2c shows the comparison between the original picked curves and the fitting curves. From this figure, we may find that the accumulated error between the fitting curves and the original curves will be large while there are many points picked.
incorrectly. For $m$ traces, we define the accumulated error as

$$E = \sum_{i=0}^{m-1} |\tau(i) - T(i)|^2.$$  \hspace{1cm} (15)

If $E$ is larger than a given threshold, the corresponding curve will be dropped. In this paper, we define the threshold as a function of the number of traces

$$Threshold = \left(\frac{m \times \Delta t}{2}\right)^2, \hspace{1cm} (16)$$

where $m$ is the number of the traces in the CRP gathers, $\Delta t$ is a time difference, in this paper, we set $\Delta t = 0.004$ s.

Figure 2d shows the final curves used to calculate the RMS velocities. The waveform stretch effects of the large offset data may lead to the large picking errors. In theory, the zero-offset traveltime and RMS velocity corresponding to an event can be calculated with just two traces. In order to avoid the picking errors and enhance the computational efficiency, we only use the traces whose offsets are in a small range to estimate the velocity model. In addition, a larger time sampling interval may lead to numerical jitter of the picked results. To avoid this situation, we use 1D interpolation along the time axis to increase the sampling rate of the seismic data before the automatic tracking. In this paper, the time sampling interval of the interpolated data is $1 \times 10^{-6}$ s.

Comparing to the NMO-based velocity analysis in the PSTM loop schedule, the maximum limitation is that it is very difficult to pick the event automatically if the events have low continuity, which mainly occurs in the case of partial offset data missing.

DATA PROCESSING WORKFLOW
For a reflector from complex structure, there is a lateral displacement between the image and its correct position if an incorrect migration velocity is used in PSTM. In this case, we should create the final velocity model in an iterative process. The detailed processing workflow includes:

1) Conduct PSTM to generate CRP gathers using an initial velocity model \( v_1 \). In the numerical test, a water velocity of 1500 m/s is used as the initial velocity.

2) Low-pass filter and interpolation are applied to the CRP gathers to smooth the data and increase its sampling rate.

3) Select an event for the first trace by calculating the trace energy in each CRP gather, and choose the time \( \tau(0) \) corresponding to the maximum energy in a sliding time window as the position of the selected event.

4) Calculate time differences between every two consecutive traces from the second trace onward as follows: compute coherence functions between consecutive traces using equation 12 trace by trace, and record the time lag that corresponds to the maximum coherence value. Then calculate the travel time curve of the selected event using equation 13.

5) Apply the least-squares curve fitting to smooth the picked curves, and then we calculate the accumulated errors between the estimated and original curves, and drop those curves whose accumulated errors are larger than a given threshold.

6) Compute zero-offset travel time \( t_0 \) and RMS velocity \( v_2 \) using least-squares method with the fitting curves, and assign the velocities to their corresponding
points in the velocity model.

7) Interpolate and smooth the velocity model with sparse values to build the updated velocity model.

8) Time migrate the seismic data to generate CRP gathers with the updated velocity model.

9) Repeat Steps 2 to 8 until the events in the CRP gathers become flat.

**NUMERICAL EXAMPLES**

To verify the feasibility of the proposed RMS velocity estimation method, we test it using the complex Sigsbee2B data and a field data set from the South China Sea.

**Sigsbee2B model test**

We apply this method to the complex Sigsbee2B NFS (no free surface) dataset. We use a PSTM Scheme following Zhang and Zhang (2014). Figure 3a shows the interval velocity model in the depth domain. This model can be separated into two parts. The left part mainly contains flat reflectors, faults and diffraction points, which can be used to analyze the behavior of the presented MVA method in simple area. The right part mainly contains a salt body with complicated geometry, and it can be used to verify the feasibility of the method to be applied to complex areas. But the multi-valued travel times caused by the two synclines may contaminate the migrated image. Because of its limitation, PSTM is insufficient to image the structure with strong lateral velocity variation.

The Sigsbee2B data set consists of 496 shots, and 348 channels per shot. The shot and receiver spacing are 46 m and 23 m, respectively. The record length is 12 s with a
sampling rate of 8 ms. We convert the velocity model from the depth domain to the
time domain (as shown in Figure 3) along vertical direction. We use a water velocity
of 1500 m/s to migrate the synthetic data set. Figure 4 shows four selected CRP
gathers at different locations with the offsets from 200 m to 4000 m. Since the first
layer's migration velocity is correct, the event of the first layer is flattened, but others
are not. Figure 5a shows the time migrated near-offset (200 m) section using the water
velocity. From this section, we find that the diffraction points, the salt top are not well
focused, and there are many diffracted waves.

We pick up and optimize the travel time curves of the events, and calculate the
RMS velocity model using least-squares method. Figure 6a shows the built velocity
model after one iteration. We migrate the data set again with the updated RMS
velocity model to generate the CRP gathers. Figure 7 shows the selected CRP gathers
at the same locations as those in Figure 4. From comparison between Figure 7 and
Figure 4, we may find that the major events become flatter in Figure 7. We show the
near-offset section (200 m) in Figure 5b from the migrated data set. By comparing
Figure 5b and Figure 5a, we see that the image quality using the updated velocity has
been greatly improved. The diffraction points and the synclinal structures are focused
much better than those shown in Figure 5a.

We update the RMS velocity model by conducting more iterations. Figure 6b
shows the RMS velocity model after four iterations, which gives a good background
shape of the salt top. We migrate the seismic data set using this velocity model. The
major events in the CRP gathers (Figure 8) are focused and flattened quite well. And
from the migrated near-offset section (Figure 5c), we find that the diffraction points, the salt top and parts of the salt bottom have been focused very well. We mute and stack all the CRP gathers from the offset 200 m to 6000 m without any other processing to obtain the final migrated image, as shown in Figure 9a. By comparison between the final migrated section with the initial interval velocity model (Figure 3b), we find that the diffraction points on the left part of the model and the salt top have been imaged accurately. Figure 9b illustrates the zoomed in section in the box of Figure 9a, from which we also see that the bottoms of the troughs are correctly positioned and some parts of the salt bottom have also been imaged very well. Comparison with published results (Figure 21 in Santos et al., 2015; Figure 9 in Reiche and Berkels, 2018) verifies that the presented method can be applied to the seismic data sets in complex areas, though the data sets contain strong coherent noises.

We test the proposed scheme on Intel Xeon processor E5-2630 (2.3 GHz) with 128 GB of DDR3 memory. In this example, approximated 3700 s is used for a thread to generate 962 CRP gathers, and approximated 40 s is used to yield the RMS velocity model. Comparing to the computational cost to generate the CRP gathers, the cost of the proposed scheme can be neglected. Moreover, the proposed scheme is not sensitive to the initial velocity.

**Field data example**

To verify the feasibility and performance of the proposed method on field data, we apply it to a real 2D field data set from the South China Sea. The shot and receiver spacing are 25 m and 12.5 m, respectively. The offset of each shot ranges from 275 m
to 3263 m. We use a water velocity of 1500 m/s to migrate the seismic data set. Figure 10a shows the CRP gathers at two different locations with the offset between 0.3-2.0 km. The event corresponding to the sea floor is flat because the initial velocity is the water velocity, but others are appeared over corrected. Figure 11a depicts the time migrated near-offset (300 m) section using the initial velocity of 1500 m/s. On this profile, the majority faults are not well focused.

We update the RMS velocity model with the proposed method and migrate the data set using this model. Figure 12a shows the estimated velocity model after one iteration. Figure 10b shows the selected CRP gathers at the same locations as those in Figure 10a. Flatness has been greatly improved for most events. We update the velocity model by more iterations. Figure 12b shows the updated RMS velocity model after four iterations, which gives a good background shape of the basin. We migrate the data set again, using the updated velocity model. Figure 10c shows the selected CRP gathers at the same locations as those in Figure 10a and 10b. From the comparison shown in Figure 10, we may find that the major events in the CRP gathers obtained using the updated velocity model after four iterations are focused and flattened very well. From the migrated near-offset section (Figure 11c), we find that the events and faults have been focused much better. In the final migrated image (Figure 13), the base of the basin can be recognized clearly. Comparing the migration result using final velocity model with the migration result using the initial velocity model, the zoomed in sections shown in Figures 14 and 15 illustrate that the faults and events have been focused much better using the final velocity model. This example
verifies that the presented MVA method can be applied to the real field data acquired in complex areas, as long as the events can be distinguished.

**DISCUSSION**

Compared with the conventional NMO-based RMS velocity analysis, the most labor-consuming part (human-interactive velocity picking) is significantly reduced in the proposed scheme by automatic event picking and velocity calculating. In the automatic event picking, the low energy and SNR of the near-offset data may lead to errors in determining the positions of the events in the first trace. In practice, we do not use the minimum offset data and enhance the amplitude and SNR of the first trace in each CRP gather by laterally stacking the amplitude of the adjacent traces. We can also determine the position of the event in the middle offset data and pick up the event by semblance scanning. With the fitting curves of the picked events, we can calculate their corresponding zero-offset travel times and RMS velocities using a least-squares approach. With the velocities at discrete grids, we can build the final RMS velocity model by spatial interpolation.

**CONCLUSIONS**

In this paper, we have presented an efficient scheme that can directly estimate the RMS velocity model without human interaction. This scheme is the numerical implementation of the conventional MVA process of PSTM. It mainly involves automatic travel time curves picking, the velocities calculating at discrete points and velocity building by interpolation and smoothing. Using fitting curves of the picked events in a small range of offsets, which is fitting a NMO correction, can prevent the
proposed scheme from local minima issue.

The proposed MVA method has been applied to the Sigsbee2B and field data sets, with a water velocity of 1500 m/s as the initial migration velocity model. The Sigsbee2B's velocity model is much more complex, and there exist multi-value travel times over the syncline. For this model, we obtain a very good velocity model after four iterations. After migration of the Sigsbee2B data set with the updated velocity model, the left part and the main shape of the salt body have been imaged quite well. This experiment demonstrates that the proposed method can generate a good velocity model even in complex areas with strong coherent noises. The real field data experiment shows the feasibility of the proposed method to process the field data set.

In both experiments, the computational cost is equivalent to that of PSTM in each iteration, and the cost of MVA process is negligible. Although the initial velocity model used in both the experiments are 1500 m/s, the high-quality velocity model and imaging results are still obtained, which demonstrates that the initial velocity is not critical to the proposed MVA scheme.

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DATA AND MATERIALS AVAILABILITY

Data associated with this research are confidential and cannot be released.