Automatic velocity analysis using bootstrapped differential semblance and global search methods*

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Abstract. The goal of automatic velocity analysis is to extract accurate velocity from voluminous seismic data with efficiency. In this study, we developed an efficient automatic velocity analysis algorithm by using bootstrapped differential semblance (BDS) and Monte Carlo inversion. To estimate more accurate results from automatic velocity analysis, the algorithm we have developed uses BDS, which provides a higher velocity resolution than conventional semblance, as a coherency estimator. In addition, our proposed automatic velocity analysis module is performed with a conditional initial velocity determination step that leads to enhanced efficiency in running time of the module. A new optional root mean square (RMS) velocity constraint, which prevents picking false peaks, is used. The developed automatic velocity analysis module was tested on a synthetic dataset and a marine field dataset from the East Sea, Korea. The stacked sections made using velocity results from our algorithm showed coherent events and improved the quality of the normal moveout-correction result. Moreover, since our algorithm finds interval velocity \(v_{\text{int}}\) first with interval velocity constraints and then calculates a RMS velocity function from the interval velocity, we can estimate geologically reasonable interval velocities. Boundaries of interval velocities also match well with reflection events in the common midpoint stacked sections.

Key words: automatic velocity analysis, bootstrapped differential semblance, interval velocity, Monte Carlo inversion, root mean square velocity constraint.

Introduction

Automatic velocity analysis has received much attention because conventional manual normal moveout (NMO) velocity analysis requires huge processing time and labour. To deal with voluminous data such as 3D (or even 2D) seismic data, automatic velocity analysis, a highly efficient processing technique, is indispensable.

One can derive not only root mean square (RMS) velocity \(v_{\text{rms}}\) but also interval velocity \(v_{\text{int}}\) through NMO velocity analysis. Interval velocities are estimated by Dix’s (1955) equation from picked RMS velocities. Toldi (1989) pointed out that certain peaks should be avoided because they might lead to non-physical interval velocities. Moreover, a small variation in the picking point in the velocity spectrum could lead to a significant change in \(v_{\text{rms}}\). Therefore, a peak-picking method that considers geologically reasonable interval velocities is necessary. In order to obtain a geologically reasonable \(v_{\text{int}}\) function, algorithms that directly estimate \(v_{\text{int}}\) functions with \(v_{\text{int}}\) constraints have been presented. Toldi (1989) proposed an automatic velocity analysis algorithm by using a linearised conjugate gradient method with \(v_{\text{int}}\) constraints to find a geologically reasonable \(v_{\text{int}}\) function. However, Toldi’s algorithm may easily become trapped in a local minimum because it utilises a linearised conjugate gradient method. Lumley (1997) used grid search and Monte Carlo methods with \(v_{\text{int}}\) constraints to get over this local minimum problem. Choi et al. (2009) showed that Lumley’s algorithm could be successfully applied to marine field data from the west coast of Africa. Even though Lumley’s algorithm achieved geologically reasonable interval velocities as well as optimal RMS velocities, there is still the possibility of picking false peaks such as multiples. In addition, the velocity spectrum calculated by conventional semblance method (Taner and Koehler, 1969) used in Lumley’s algorithm has low velocity resolution at later times.

In this study, we have developed a new automatic velocity analysis algorithm based on Lumley’s algorithm (1997). The algorithm we have developed utilises bootstrapped differential semblance (BDS) (Abbad et al., 2009), which can significantly improve the velocity resolution, instead of conventional semblance in creating velocity spectrum. Moreover, a new RMS velocity constraint and the conditional determination of the initial \(v_{\text{rms}}\) are implemented to prevent picking multiples and to enhance the efficiency, respectively.

Algorithm of automatic velocity analysis

The velocity analysis algorithm in this study consists of three steps (Figure 1). In the first step, a velocity spectrum is constructed from a common midpoint (CMP) gather by using the BDS method. Then, the summation of semblance peaks for each time sample on the velocity spectrum (BDSmax) is calculated.

In the second step, the initial \(v_{\text{rms}}\) function is determined as a simple function approximated by the peak BDS values or the best \(v_{\text{rms}}\) velocity function of the previous CMP gather. The determined initial \(v_{\text{rms}}\) function is converted to an initial \(v_{\text{int}}\) velocity function because the interval velocities, not RMS velocities, are perturbed during Monte Carlo inversion in the next step.

In the last step, by using the Monte Carlo method, the initial \(v_{\text{int}}\) function is perturbed under three constraints to get geologically

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reasonable interval velocities (Choi et al., 2009). One is a global range constraint that guides a lower and upper limit of $v_{\text{int}}$. Another is a local range constraint that makes a perturbation remain within a certain percentage of the initial guess. The other constraint prevents abrupt vertical changes of $v_{\text{int}}$. Moreover, at this stage, the acquired $v_{\text{rms}}$ peaks are checked to see whether they are true or false peaks with a new $v_{\text{rms}}$ constraint implemented in our automatic velocity analysis module. Then, by the sum of BDS values along the $v_{\text{rms}}$ function, BDSMC, the following objective function, $E$, is calculated:

$$E = 1 - \frac{\text{BDS}_{\text{MC}}}{\text{BDS}_{\text{max}}}.$$  \hfill (1)

Among all the BDSMC values obtained by the perturbed $v_{\text{int}}$ functions, the $v_{\text{int}}$ function that minimises the objective function in equation 1 and its corresponding $v_{\text{rms}}$ function is chosen as the final best solution.

**Bootstrapped differential semblance**

To focus the peaks at later times and to improve the accuracy of the RMS velocity estimation, our automatic velocity analysis uses BDS (Abbad et al., 2009) in creating the velocity spectrum. Since results of automatic velocity analysis depend heavily on a coherency estimator, an estimator that provides a high velocity resolution is essential. Even though the conventional semblance method, which is the most popular coherency estimator (Taner and Koehler, 1969), provides a robust velocity spectrum, the tendency to smear the velocity peaks as time increases makes difficult the estimation
of peaks at later times by an automatic velocity analysis module. Recently, Abbad et al. (2009) proposed a new coherency measure, BDS, which can estimate the time-related reflection parameters. In the BDS method, the bootstrap procedure (Sacchi, 1998) was applied to the differential semblance (Symes and Carazzone, 1991; Brandsberg-Dahl et al., 2003), which focuses on the differences between adjacent traces along a hyperbolic trajectory in a CMP gather. The term, bootstrapping, is defined as a random rearrangement of offset-ordered seismic traces in a CMP gather. The equation for calculating BDS is

$$\text{BDS} = \frac{\sum_{i=1}^{N} \sum_{t=t_0}^{t_0+\frac{1}{l}} [d(t, \tau_i) - d(t, \tau_{i-1})]^2}{2(N-1) \sum_{i=1}^{N} \sum_{t=t_0}^{t_0+\frac{1}{l}} d(t, \tau_i)^2}$$

where $d(t, x)$ is time-offset domain data; $\tau_i$ is the bootstrapped series of offsets, obtained by random sorting of the traces; $N$ is the number of traces; and $\lambda$ is the width of the time window. Compared with conventional semblance, BDS provides higher velocity resolution in the velocity spectrum because BDS considers differences in the amplitude of the seismic data randomly ordered along hyperbolic trajectories. Figure 2 shows the velocity spectra created by conventional semblance (Figure 2b) and BDS (Figure 2c) for a CMP gather of the synthetic seismic data used in this study (Figure 2a). As shown in Figure 2, the velocity spectrum obtained by the BDS method shows more discriminable peaks for reflection events than those estimated by the conventional semblance method.

**Determination of the initial $v_{\text{rms}}$ and $v_{\text{int}}$**

To reduce running time and obtain optimal results, the use of initial velocity functions close to the true solutions is very important. For this purpose, a new Monte Carlo inversion step is proposed, as shown in Figure 3. The detailed flow chart of the Monte Carlo inversion step with a new $v_{\text{rms}}$ constraint is as follows:

1. **Initial interval velocity function from Grid search**
2. **Check velocity range constraints (Local & Global)**
3. **Divide layers**
4. **Check velocity difference constraint**
5. **Estimate interval velocity**
6. **Calculate corresponding $v_{\text{rms}}$**
7. **Check $v_{\text{rms}}$ constraint**
   - **Random step**
   - **Random walk**
8. **Check convergence condition 1**
   - **Yes**
   - **No**
9. **Check convergence condition 2**
   - **Yes**
   - **No**
10. **Output ($v_{\text{rms}}^*, v_{\text{int}}^*$)**

**Fig. 3.** Detailed flow chart of the Monte Carlo inversion step with a new $v_{\text{rms}}$ constraint.

**Fig. 4.** Velocity model including faults.

**Table 1.** The parameters used in creating the synthetic data with a velocity model including faults.

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<tr>
<td>Sampling interval</td>
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Fig. 5.  (a) A common midpoint gather located at ~17 km (indicated by a black arrow in Figure 4).  (b) A $v_{rms}$ function (black solid line) estimated by Lumley’s automatic velocity analysis using conventional semblance.  (c) A $v_{rms}$ function (green solid line) estimated by our automatic velocity analysis using bootstrapped differential semblance (BDS) without the $v_{rms}$ constraint.  (d) A $v_{rms}$ function (blue solid line) estimated by our automatic velocity analysis using BDS with the $v_{rms}$ constraint.

Fig. 6.  Normal moveout-corrected common midpoint gathers by applying the $v_{rms}$ function estimated with Lumley’s algorithm (a) and by applying the $v_{rms}$ function estimated with our algorithm using the $v_{rms}$ constraint (b).
important. In Lumley’s algorithm (1997), initial velocity functions were approximated by simple functions (equation 3) by a grid search method. Using a grid search method, the initial RMS velocity function is approximated by the following simple function (Lumley, 1997):

\[ v_{nms} = v_0 + 2t^\beta, \]  

(3)

where the \( v_0 \) is the \( v_{nms} \) at time zero; \( \alpha \) is related to the RMS velocity gradient; and \( \beta \) is related to the rate of increase or decrease in velocity with time. The best parameter set \( \{v_0^*, \alpha^*, \beta^*\} \) is obtained by grid search when the path of the RMS velocity function (equation 3) on the velocity spectrum maximises the sum of BDS values along it. The determined initial \( v_{nms} \) function is converted to an initial \( v_{int} \) velocity function because the interval velocities, not RMS velocities, are perturbed during Monte Carlo inversion in the next step. Using equation 3, an analytic expression for the interval velocity, \( v_i \), can be obtained by Dix’s equation as follows:

\[ v_i = \sqrt{v_0^2 + 2v_0\alpha(1 + 2\beta)t^\beta + (1 + 2\beta)^2\alpha^2t^{2\beta}}. \]  

(4)

Even though a simple function obtained by grid search gives a quite reasonable guess, the determination of the initial velocity consumes roughly a quarter of the whole processing time. The initial velocity functions were approximated by simple functions (equation 3) by a grid search method. Using a grid search method, the initial RMS velocity function is approximated by the following simple function (Lumley, 1997):

\[ v_{nms} = v_0 + 2t^\beta, \]  

(3)

where the \( v_0 \) is the \( v_{nms} \) at time zero; \( \alpha \) is related to the RMS velocity gradient; and \( \beta \) is related to the rate of increase or decrease in velocity with time. The best parameter set \( \{v_0^*, \alpha^*, \beta^*\} \) is obtained by grid search when the path of the RMS velocity function (equation 3) on the velocity spectrum maximises the sum of BDS values along it. The determined initial \( v_{nms} \) function is converted to an initial \( v_{int} \) velocity function because the interval velocities, not RMS velocities, are perturbed during Monte Carlo inversion in the next step. Using equation 3, an analytic expression for the interval velocity, \( v_i \), can be obtained by Dix’s equation as follows:

\[ v_i = \sqrt{v_0^2 + 2v_0\alpha(1 + 2\beta)t^\beta + (1 + 2\beta)^2\alpha^2t^{2\beta}}. \]  

(4)

The term, \( \sigma \), indicates the degree of similarity between BDS_{pv} and BDS_{spw}, which are the summation of BDS values along the best \( v_{nms} \) function of the previous CMP gather and that of the present CMP, respectively (Figure 1). If BDS_{spw} does not satisfy the condition in equation 5 or if there is no previous CMP gather to compare, an initial \( v_{nms} \) function will be determined by the grid search method.

**RMS velocity constraint to prevent picking multiples**

In the Monte Carlo inversion step, we use a new \( v_{nms} \) constraint to avoid picking false peaks unrelated to true events as well as three \( v_{nms} \) constraints proposed by Lumley (1997).

Since multiples included in the data produce peaks in the velocity spectrum and make NMO velocity analysis difficult, we expect them to be removed before NMO velocity analysis. However, even though the data go through multiple-suppressing processing, some multiples may still remain. In that case, it is a general strategy for data processors to pick \( v_{nms} \) increasing with time in NMO velocity analysis, because peaks due to multiples are observed straight down from peaks of the primary reflections on the velocity spectrum. In our module, a \( v_{nms} \) Constraint, which picks \( v_{nms} \) in the direction of increasing velocity, will be applied if the input data is considered to be contaminated by multiples (Figure 3).

**Numerical example**

To verify our automatic velocity algorithm, we have applied our algorithm to a synthetic dataset obtained with a velocity model simulating the subsurface of the west coast of Africa. The velocity model consists of several crooked layers with some faults (Figure 4). We obtained 4321 CMP gathers with full-fold coverage by using finite-difference modelling methods (Falk et al., 1996). The parameters used in creating the synthetic data are shown in Table 1.

Choi et al. (2009) concluded that Lumley’s algorithm was successfully applied to the synthetic dataset from the velocity model shown in Figure 4. However, the velocity spectra of CMP gathers around the fault include false peaks due to the fault. Figure 5a shows a CMP gather located at ~17 km. When we constructed a velocity spectrum from this CMP gather by the conventional semblance method, many false peaks are produced (marked by a black circle in Figure 5b) and they hinder the automatic velocity analysis module from picking the true RMS velocities. Even though peaks on the velocity spectrum have no physical meaning, the automatic velocity analysis algorithms tend to chase higher peaks. Thus, the accuracy of their results is more dependent on the velocity spectrum used for finding the \( v_{nms} \) function than manual velocity analysis. Figure 5c shows the velocity spectrum generated by BDS implemented on our module. As shown in Figure 5c, many false peaks are removed, but the wrong \( v_{nms} \) function is still obtained because of the remaining false peaks. To overcome this problem, the velocity analysis was applied with the RMS velocity constraint (Figure 5d). As shown in Figure 5d, with the RMS velocity constraint, the true peaks have been successfully picked.

Figure 6 presents CMP gathers after applying NMO correction to the CMP gather in Figure 5a by using the RMS velocity function obtained by Lumley’s algorithm (Figure 6a) and our algorithm using the \( v_{nms} \) constraint (Figure 6b), respectively. The reflection events in Figure 6b are better flattened, especially at later times, than those in Figure 6a.

The final CMP stacked sections resulting from using RMS velocity functions obtained by both automatic velocity algorithms (Figure 7b and c) show more coherent reflection events than those in the stacked section resulting from RMS velocity functions estimated by manual velocity analysis (Figure 7a). Comparing the CMP stacked section using RMS velocity functions estimated by our new module (Figure 7c) to that by Lumley’s algorithm (Figure 7b), events between 5 s and 6 s (indicated by a black arrow) in Figure 7c show better continuity and more similarity to corresponding events in Figure 7a than those in Figure 7b. Since those false peaks affected by the fault (shown in Figure 5) are successfully avoided by the \( v_{nms} \) constraint in the picking processing, more accurate results have been achieved. In Figure 8, interval velocity sections obtained by manual velocity analysis, Lumley’s algorithm, and our automatic velocity analysis algorithm have been presented. As shown in Figure 8, the sections estimated by automatic velocity analysis algorithms are more sensitive to velocity structure than those from manual velocity analysis (Figure 8a). Moreover, the interval velocity section (Figure 8c) resulting from the proposed algorithm is closer to the true velocity model shown in Figure 4 than that from Lumley’s algorithm. Furthermore, the area distorted by faulting (black circle) in the interval velocity section is shrunk (Figure 8c) compared to that by Lumley’s algorithm (Figure 8b).

**Marine field data**

We have applied our automatic velocity analysis module to full-fold CMP gathers of marine field data from the East Sea of Korea. Survey parameters are shown in Table 2. Simple pre-
processing was applied to the data before velocity analysis: mute of the direct arrivals and 10–80 Hz bandpass filtering. Since the water depth is deeper than 2 km, multiples begin to appear quite separately from primary reflections. Thus, we have used the data before 4.7 s only.

One of CMP gathers from the field dataset and its BDS velocity spectrum are represented in Figure 9a and b. Our automatic velocity analysis module has created an optimal $v_{\text{rms}}$ function, which made all reflection events almost flat after NMO correction (Figure 9c). The results of CMP stacking by using RMS velocity functions resulting from manual velocity analysis and from the proposed algorithm are shown in Figure 10. To get the RMS velocity functions by manual velocity analysis every 20th CMP (189 CMP gathers total) were used. The proposed automatic velocity analysis was applied to 3765 CMP full-fold gathers. We could cut the processing time by 16% with the conditional initial velocity-determination strategy, compared with that without such a strategy. Reflection events in the CMP stacked sections have similar continuities overall. When the interval velocity section estimated by manual velocity analysis (Figure 11a) is compared with that estimated by the new algorithm (Figure 11b), the interval velocity section from our new algorithm is more sensitive to subsurface velocity structure. Especially, as shown in Figure 9b, the events around 3.5 s match well with the velocity boundaries.

### Table 2. Survey parameters for a marine field dataset from the East Sea of Korea.

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Conclusions

We have developed an automatic velocity algorithm using the BDS technique and global search methods. Because of the enhancement of resolution of the velocity spectrum by the BDS method, more accurate $v_{rms}$ functions can be estimated. In addition, a grid search step which determines the initial velocity is skipped when lateral changes of subsurface structures are subtle, and the best result obtained in the

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Fig. 9. (a) A representative common midpoint (CMP) gather of marine field data. (b) The $v_{rms}$ function estimated by our automatic velocity analysis on bootstrapped differential semblance velocity spectrum. (c) A CMP gather after applying normal moveout correction to the CMP gather in Figure 9a using the optimal $v_{rms}$ function in Figure 9b.

Fig. 10. Common midpoint stacked sections by using the velocity function obtained with manual velocity analysis (a), and with the developed automatic velocity analysis (b) for the marine field data.

Fig. 11. Interval velocity sections obtained with manual velocity analysis (a), and with the developed automatic velocity analysis (b) for the marine field data.
previous CMP is used as the initial velocity to estimate present CMP to reduce the running time. Furthermore, a new RMS velocity constraint is implemented in the module in order to avoid picking false peaks such as multiples.

We have demonstrated that many false peaks in the velocity spectrum obtained by conventional semblance were removed in the BDS velocity spectrum for the synthetic dataset. In addition, the RMS velocity constraint helps our velocity analysis module to avoid picking false peaks in CMP gathers near faults so that events are successfully flattened after NMO correction. Finally, the CMP stacked section and the interval velocity section derived by applying our newly developed automatic velocity module to marine field data show coherent events and a geologically reasonable interval velocity section.

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고해상도 속도스펙트럼과 전역탐색법을 이용한 자동속도분석
최형욱 1, 변중무 2, 설순지 1

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요 약: 자동속도분석의 목적은 대용량 탄성파탐사자료로부터 정확한 속도를 효율적으로 추출하는 것이다. 본 연구에서는 bootstrapped differential semblance (BDS) 방법과 몬테카를로 역산법을 이용하여 효율적인 자동속도분석 알고리즘을 개발하였다. 자동속도분석을 통해 보다 정확한 결과를 계산하기 위하여 우리가 개발한 알고리듬에서는 일반적인 채널간스보다 높은 속도해상도를 제공하는 BDS를 일관성 측정법으로 사용하였다. 계수가 개발된 자동속도분석 알고리즘의 처리시간을 줄이고, 효율성을 증가시키기 위해 조건적으로 초기속도모델을 결정하는 단계를 추가하였다. 그리고 잘못된 피크값을 평창하는 문제를 방지하기 위해서 새로운 RMS 속도제거조건을 선력적으로 사용하였다. 개발된 자동속도분석 모델의 성능을 시험하기 위해서 합성탄성파탐사자료와 동등에서 취득한 현장자료에 개발된 모델을 적용하였다. 본 연구에서 개발된 알고리듬을 통해 얻은 속도결과를 적용하여 분산 중합단변은 일관된 변수이드들과 NMO보정 결과의 질이 향상된 것을 보여준다. 더욱이, 개발된 알고리듬은 구간속도제거조건을 확인하면서 구간속도를 먼저 구하고 이를 이용하여 RMS 속도를 계산하기 때문에, 기밀적으로 다양한 구간속도를 구할 수 있다. 또한, 구간속도의 경계들이 중합단변에서 나타나는 변수이드들과 잘 부합된다.

주요어: 자동속도분석, bootstrapped differential semblance (BDS), 구간속도, RMS, 속도제거조건, 몬테카를로 역산

부트스트랩差分センブランスおよびグローバル検索を用いた自動速度解析
崔 亨旭・邊 重茂・薛 順智

1 漢陽大学校

要 旨: 自動速度解析では、膨大な地球探査データから正確な速度を効率的に抽出することが目標である。この研究では、ブートストラップ差分センブランス (BDS) とモンテカルロ・インバージョンを用いた、効率的な自動速度解析アルゴリズムの開発を行った。自動速度解析により正確な結果を導出するため、我々が開発したアルゴリズムでは従来のセンブランスより高分解能な速度決定が可能なBDSを、コーヒーレーン推定に用いた。さらに、我々の提案する自動速度解析モジュールでは条件付きの初期速度決定ステップを導入しているため、高速な計算が可能である。誤ったピーク選択を防ぐRMS速度制約が新たにオプションとして使用されている。数値データおよび日本海で取得された海洋のフィールドデータを用いて、開発された自動速度解析モジュールの検証を行った。我々のアルゴリズムにより求められた速度結果を用いた重合断面にはコーヒーレントなイベントが見られる。また、その速度を用いる事により、NMO補正結果の品質も同様に向上した。さらに、我々のアルゴリズムでは、まず区間速度制約を用いた上で区間速度 (vₚ) を求め、その区間速度を用いてRMS速度機能を計算するため、求められた区間速度は地質学的に妥当なものとなる。区間速度の境界はCMP重合断面の反射イベントと良く一致する。

キーワード: 自動速度解析, ブートストラップ差分センブランス(BDS), 区間速度, RMS速度制約, モンテカルロ・インバージョン

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