COMPARISON BETWEEN NORMALIZED CROSS-CORRELATION AND SEMBLANCE COHERENCY MEASURES IN VELOCITY ANALYSIS

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ABSTRACT

The prime objective of velocity analysis is the correct estimation of the stacking velocities, so that the normal move out (NMO) correction done in the subsequent processing steps can be accurate. Velocity analysis is popularly done with the help of velocity spectrum. Increasing the resolution of the velocity spectrum can help in better estimation of velocities. In this work, a comparison is done between the semblance, and the normalized cross-correlation sum measure of coherency. These two coherency measures are applied on simple synthetic datasets, and the Sigsbee2A data. Based on the results of the application, normalized cross-correlation sum provided better resolution and estimation of velocities than the semblance method in most of the cases. The normalized cross-correlation sum method is particularly better in cases where the velocities of two events are very close to each other. Also, the background noise in the velocity spectrum is considerably less in case of the normalized cross-correlation method than the semblance method which contributes to the enhanced resolution of the events. The secondary events like multiples and diffractions are clearly distinguished in case of normalized cross-correlation sum method than the semblance method. The computation time of both of these methods are comparable.

INTRODUCTION

Velocity analysis is one of the first steps in seismic processing. It is a vital step in processing as the subsequent processing steps are dependent on the correct velocity estimation. The standard approach for estimating stacking velocities is to pick maxima in some coherence measure at fixed zero-offset reflection times (Yilmaz, 2001). With the estimated velocities, the reflection travel-times for non-zero offsets can be corrected, and compress the recorded data volume to a stacked section. Velocity analysis is commonly based on the computation of the velocity spectrum (Taner and Koehler, 1969). In this, some measure of signal coherency is displayed on a graph of velocity versus two-way zero-offset time known as velocity spectrum. Stacking velocities are chosen from the velocity spectrum, from the points corresponding to the highest coherency, at times with significant event amplitudes. A peak in the spectrum denotes the velocity corresponding to a hyperbolic move-out that fits the data relatively well at that zero-offset time and velocity.

The prime objective of estimation of correct velocities can be attained by increasing the accuracy and the resolution of the velocity spectrum. In case of events with conflicting dips, or with the reflection events very close to each other, or weak primaries in the presence of strong multiples, the velocity estimation can be challenging. In such cases, the selection of the correct coherency measure for velocity analysis is essential.

An increase in resolution in velocity estimation using various approaches has been proposed by different workers (Kirling et al., 1984; De Vries and Berkhout, 1984; Toldi, 1989; Biondi and Kostov, 1989). Among the various approaches proposed, coherency measure is the most popular one. Different approaches in the coherency measure of velocity estimation have also been adapted at different times (Neidell and Taner, 1971; Larner and Celis, 2007; Luo and Hale, 2010). The most commonly used coherency measure in velocity analysis technique is the semblance method. In this work, velocity analysis is done using the normalized cross-correlation sum method, and the semblance method. The former method is based on the cross-correlation of the adjacent traces, whereas the latter is based on the cross-correlation of the traces. An attempt is made to compare the velocity estimation from each of these methods.

METHODS

In this work, the velocity analysis is primarily done using the cross-correlation sum and semblance coherency method. In order to establish a better comparison between the two methods, the normalized cross-correlation sum is used, since semblance also gives normalized coefficients. The basic principle underlying these methods is discussed in brief in this section.

Semblance

Conventional semblance was first defined by Taner and Koehler (1969) as the normalized ratio of the output to the input energy. It can also be defined as the ratio of the energy of the stacked trace divided by the energy of all the traces that make up the stack. It is the most commonly used method for the estimation of NMO velocity as a function of two-way offset time. The semblance coefficient as defined by Neidell and Taner (1971) is given by

$$S_c = \frac{\sum\limits_{j=k-(N/2)}^{k+(N/2)} \left\{ \sum\limits_{i=1}^{M} f_{i,j(i)} \right\}^2}{M \sum\limits_{j=k-(N/2)}^{k+(N/2)} \sum\limits_{i=1}^{M} f_{i,j(i)}^2} \quad , \tag{1}$$

where, i is the trace number, j and k are the time sample indices, $f_{i,j(i)}$ is the amplitude of the j-th sample in the i-th trace of the NMO corrected gather, M is the number of traces. The outer sum is done over a time-smoothening window with length $N+1$ centered at the time index k. The semblance coefficient is normalized by dividing it with the number of traces (M). The value of the S_c lies between 0 and 1. If the data from all channels are perfectly coherent, or show continuity from trace to trace, then the semblance has a value of unity.

NORMALIZED CROSS-CORRELATION SUM

In this method, all possible cross-correlations trace pairs in a CMP gather are summed for each trial velocity and zero-offset two way travel time inside a time window. The time window of $(N+1)$ samples for each trace is chosen such that it is symmetrical to the sample $k(i)$. The un-normalized cross-correlation sum coefficient between two traces p channel index units apart, as defined by Neidell and Taner (1971) is given as

$$UCC_s = \frac{2}{M(M-1)} \sum_{j=k-(N/2)}^{k+(N/2)} \sum_{p=1}^{M-1} \sum_{i=1}^{M-p} f_{i,j(i)} f_{i+p,j(i+p)} \quad , \tag{2}$$

The term $M(M-1)/2$ denotes the total number of cross-correlations for each trial velocity and zero-offset two-way travel time.

The normalizing of the above coefficient (2) by dividing each cross-correlation trace pair by the geometric mean of the energy, of each trace pair chosen in the cross correlation, inside the chosen time window, gives us the normalized cross-correlation sum. It was defined by Neidell and Taner (1971), and is given as

$$NCC_s = \frac{2}{M(M-1)} \frac{\sum_{j=k-(N/2)}^{k+(N/2)} \sum_{p=1}^{M-1} \sum_{i=1}^{M-p} f_{i,j(i)} f_{i+p,j(i+p)}}{\sqrt{\sum_{j=k-(N/2)}^{k+(N/2)} f_{i,j(i)}^2 \sum_{j=k-(N/2)}^{k+(N/2)} f_{i+p,j(i+p)}^2}}, \tag{3}$$

The above coefficient (3) can also be normalized using the arithmetic mean instead of the geometric mean. An important distinction between the two methods of normalization is that, the normalization using arithmetic mean will make the coefficient to be dependent on the likeness and the phase of the signal in the two channels that are being considered. This dependence of the coefficient on the scaling of the data channels may not be desirable depending on the intended application. The values of the normalized coefficients lie between 0 and 1; with 0 indicating least coherency, and 1 being perfectly coherent.

RESULTS AND DISCUSSIONS

We compare the results of the above mentioned coherency measures for various synthetic data of models prepared, and also CMP gathers from the Sigsbee2A dataset.

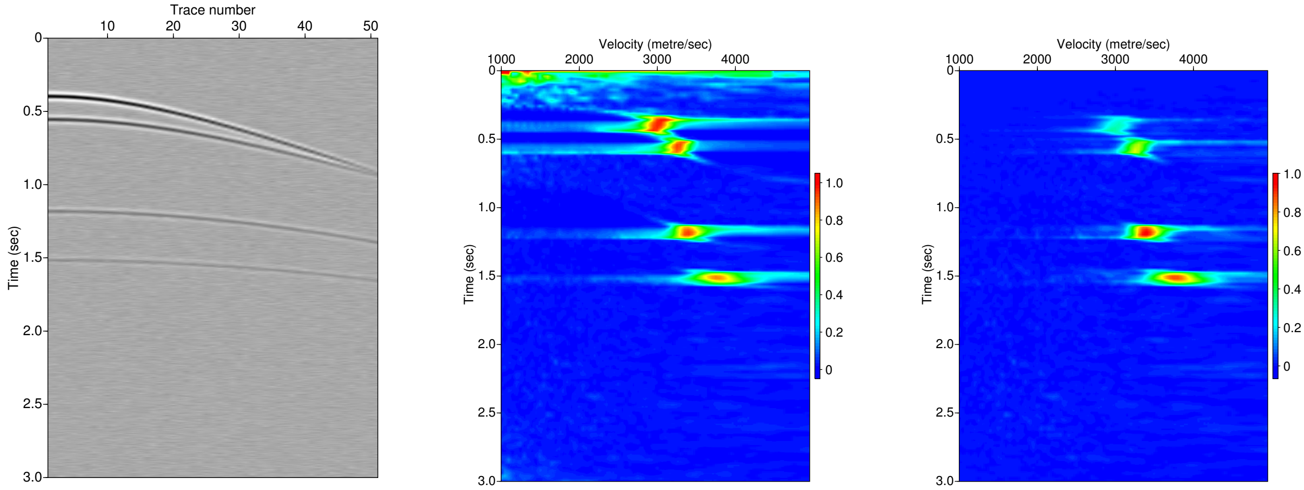
Synthetic datasets

The data sets were generated using the Seismic Unix software package. Gaussian noise was added with SN=20. In this study the parameters used for the velocity analysis for each example are kept the same so that they can be better compared.

The synthetic CMP gather (Figure 1a) is of a homogenous, isotropic layered earth. The CMP fold is 51, and the sampling interval is 4msec, with the total recording length as 3sec. There are four major events in the data. All the events of the data were identified clearly in the semblance velocity spectrum (Figure 1b) and the normalized cross-correlation spectrum (Figure 1c). The next dataset (Figure 2a), is a modification of the previous model, where a conflicting dip case is shown by replacing one of the layer in the above model with a high velocity layer. Both coherency methods (Figures 2b and 2c) yielded similar types of results. However, the cross-correlation spectrum yielded a better resolution. The zone of maximum coherency which represents primary events in the spectrum is smeared in case of semblance plot. However, in case of normalized cross-correlation sum, these zones are less smeared and hence automatic picking of maxima will be easier in case of normalized cross-correlation sum plot than semblance plot. In another dataset (Figure 3a), multiples are included to test the efficiency of the methods in the presence of multiples. The CMP fold of the data is 119, and the sampling interval is 4msec with the total recording length of 3sec. In this case, the major events were distinct in the semblance spectrum (Figure 3a). However, the multiples were more distinct in the cross-correlation plot (Figure 3c). These multiples occur in both the plots, and can be clearly identified in the spectrum as they have lesser velocities than the corresponding main events. The multiples can be seen distinctly at around 0.75 sec with approximate velocity of 1500 m/sec, and around 1.25 sec with approximate velocity of 1650 m/sec. These two multiples and the continuing trail in the spectrum is easy to decipher in the cross-correlation spectrum than the semblance spectrum.

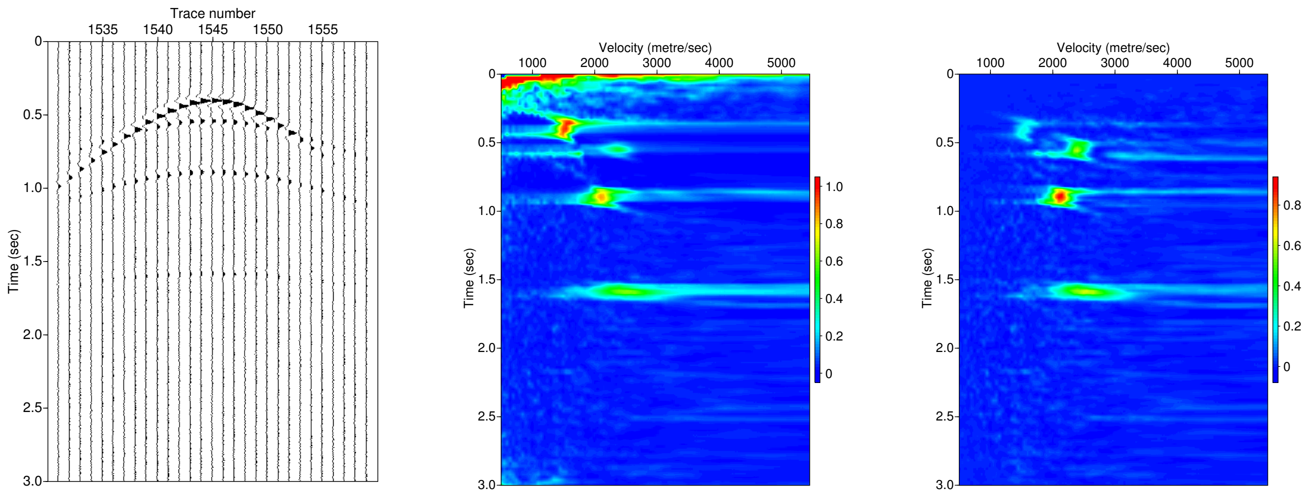
Sigsbee2A datasets

The Sigsbee2A is a synthetic constant density acoustic dataset released in 2001 by the "SMAART JV" consortium (Paffenholz et al., 2002). It is a synthetic model of the geologic setting of the deepwater Gulf of Mexico. The data consists of a salt dome structure, apart from number of normal faults and thrust faults. Two CMP gathers are chosen for the velocity analysis, one without the salt dome structure (Figure 4a) and another with the salt dome structure in it (Figure 5a). The CMP fold in each of the data is 87, and the sampling rate is 8msec with a total recording time of 12sec. A considerable amount of preprocessing of the datasets is done before the velocity analysis, like muting of first arrivals. The results of the semblance for the datasets are given in figures 4b and 5b, and that for the normalized cross-correlation sum are given



(a) (b) (c)

Figure 1: (a) A synthetic common midpoint gather having four events; (b) semblance, (c) normalized cross-correlation sum velocity spectrum.



(a) (b) (c)

Figure 2: (a) A synthetic common midpoint gather having events with conflicting dips; (b) semblance, (c) normalized cross-correlation sum velocity spectrum.

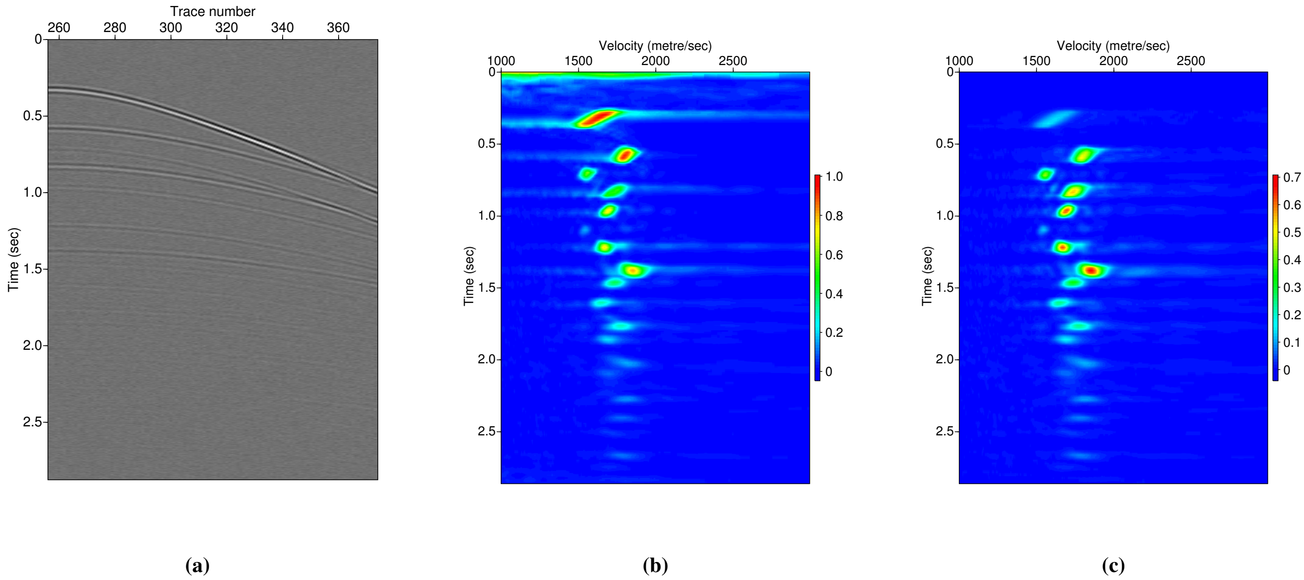


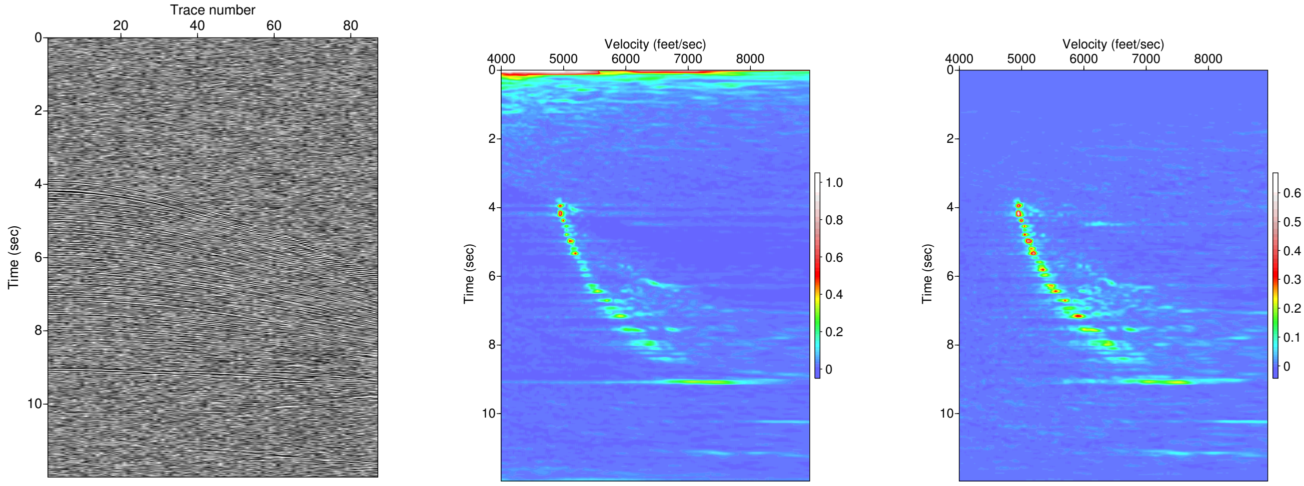
Figure 3: (a) A synthetic common midpoint gather having events and multiples; (b) semblance, (c) normalized cross-correlation sum velocity spectrum.

in figures 4c and 5c. The comparison of the two coherency measures shows similar kind of results in both the datasets. The trends of the velocity variation can be easily picked up in both the cases. However, the resolution in case of the normalized cross-correlation is slightly improved as compared to the semblance spectrum. Also, the diffractions and multiples are visible in the normalized cross-correlation sum than the semblance spectrum. In the semblance spectrum and normalized cross-correlation spectrum of Figure 4, it is clear that the points of highest coherency for the late events from 6 sec to 9 sec can be easily picked from the normalized cross-correlation sum spectrum (Figure 4c) than in the semblance spectrum (Figure 4b). Also, the diffraction events are more prominent in the cross-correlation sum spectrum (Figure 4c) than the semblance spectrum (Figure 4b). One of such diffraction event can be easily seen at around 4.75 sec with an approximate velocity of 6000 ft/sec in the normalized cross-correlation sum spectrum. The semblance spectrum (Figure 4b) fails to identify this event. These diffraction events are marked in Figure 4c. In the spectrum of the complex dataset shown in Figure 5, the multiples at around 5.5 sec with an approximate velocity of 6000 ft/sec is distinct for the normalized cross-correlation sum spectrum (Figure 5c) than in the semblance spectrum (Figure 5b). The multiples, distinct in the normalized cross-correlation sum spectrum are clearly indicated in Figure 5c.

CONCLUSIONS

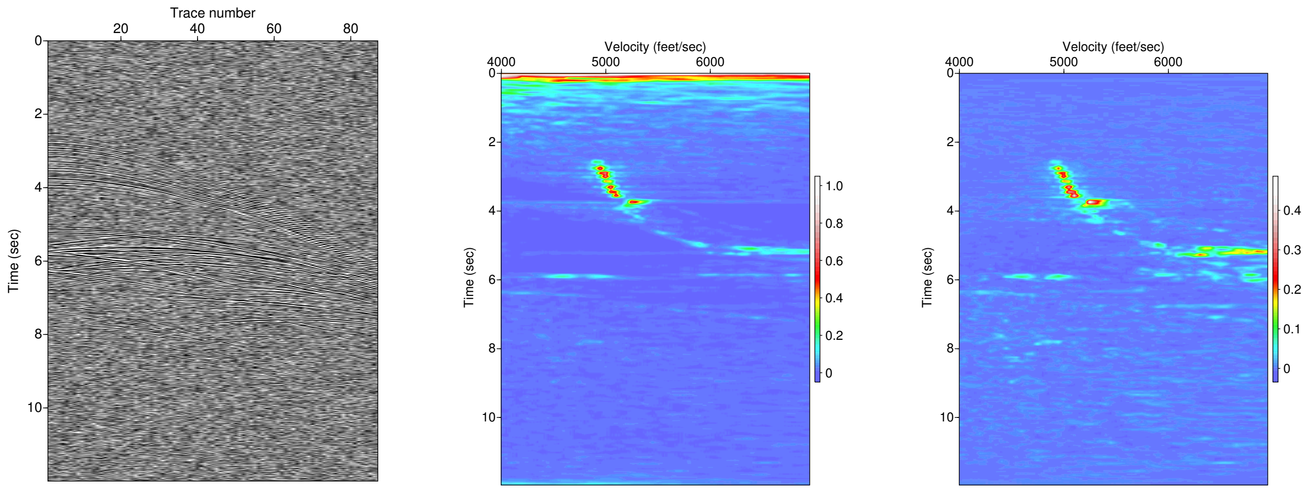
Both normalized cross-correlation sum and semblance method is based on the coherency of the traces taken into consideration within a time window. The results of both of these coherency measures on synthetic datasets provided equivalently good velocity estimation. However, a close look into both the spectra for each of the datasets, reveal the resolution to be better in case of the cross-correlation measure than the semblance spectrum. The background noise is less in the cross-correlation plot as compared to the semblance plot which also contributes to the resolution enhancement. The secondary events like multiples, diffractions were better distinguishable in case of normalized cross-correlation spectrum than the semblance spectrum.

An enhanced resolution of the velocity spectrum is highly desirable in the automatic picking of the events of high coherency for velocity estimation. It is very early to make a stern comment that normalized cross-correlation method is always better than the semblance method in terms of the resolution of the events. However, in the analysis made in this work, normalized cross-correlation provided better results in



(a) **(b)** **(c)**

Figure 4: (a) A common midpoint gather of Sigsbee2A model (left part), simple stratification with faults and diffractions; (b) semblance, (c) normalized cross-correlation sum velocity spectrum. The diffraction events in Figure 4c are not clear in Figure 4b.



(a) **(b)** **(c)**

Figure 5: (a) A common midpoint gather of Sigsbee2A model (right part), complex stratification with salt domes, faults and diffractions; (b) semblance, (c) normalized cross-correlation sum velocity spectrum. The multiples are more distinct in the normalized cross-correlation sum plot (Figure 5c) than in the normalized cross-correlation plot (Figure 5b).

most of the cases than the semblance method. It might be interesting to include further coherency measures in the study to better estimate the dependence of the velocity analysis on the coherency measure.

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