MINIMUM SEMBLANCE: A MODIFIED COHERENCE MEASURE TO IMPROVE THE RESOLUTION OF SEMBLANCE SECTIONS

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ABSTRACT

Coherence measures, the most universally used being semblance, represent a well-known tool in seismic processing to determine the position of seismic events in a multitude of applications. A frequent complaint is low resolution, i.e., high measures in the vicinity of the ideal parameter values. Minimum Semblance is an alternative method to determine the coherence of seismic events, designed to increase the resolution of the resulting semblance sections. The idea is to utilize the minimum value of several semblance calculations within a time window. The computational cost of minimum semblance is comparable to that of conventional semblance and significantly lower than that of weighted or AB semblance. We apply minimum semblance to stacking-velocity analysis and compare its behaviour to these other coherence measures. Our results show that minimum semblance increases resolution. For field data, our approach presented comparable results to AB semblance in that the resulting NMO correction shows similarly well flattened events. We also highlight the fact that Minimum Semblance preserves its resolution as the time-window size is increased, in this way becoming less dependent on the choice of the window size than conventional and weighted semblances.

INTRODUCTION

Since the famous work of Taner and Koehler (1969), semblance has been a reliable measure of coherence in seismic processing. As a coherence measure, semblance is mostly used to detect events in noisy multiple-coverage data. Semblance is known to depend in various degrees on operator size (aperture and window length) and noise level (Douze and Laster, 1979). Furthermore, it supposes white-noise data contamination and constant amplitude along reflection curve. Therefore, this function can show unpredictable behaviour if the noise is colored. For this reason, many attempts have been made to find a more stable measure which has less dependence on the type of noise or the choice of parameters used in the analysis. Conventional semblance has been the best coherence measure in virtually all attempts, because it is robust and easy to calculate in almost all situations. However, there are specific cases where other measures may be more advantageous.

Weighted Semblance (Luo and Hale, 2012) is a direct extension of the conventional measure. It uses a weighting function chosen to emphasize terms that are more sensitive to changes in velocity, resulting in increased resolution of the semblance section. Counterintuitively, resolution increases when choosing an offset-dependent weighting function that minimizes semblance. AB Semblance, introduced by Sarkar et al. (2001, 2002) and implemented by Fomel (2009) is interpreted as a correlation measure with an amplitude trend and is particularly attractive for data presenting polarity reversal.

Inspired by Weighted Semblance, we apply the minimization idea to conventional semblance. The resulting Minimum Semblance increases the resolution of the latter, while preserving its advantages, including robustness and low computational cost. The main goal of this work is to analyze and compare the different semblances functions in common midpoint (CMP) sections in order to determine which measure provides the best velocity spectra. Synthetic and field data were used for this purpose.

METHOD

Conventional Semblance is a quantitative coherence measure introduced by Taner and Koehler (1969). Its mathematical expression is given by

$$S = \frac{\sum\limits_{j=-M}^{M} \left(\sum\limits_{i=1}^{N} u_{i,j} \right)^2}{N \sum\limits_{j=-M}^{M} \left(\sum\limits_{i=1}^{N} u_{i,j}^2 \right)}, \tag{1}$$

where $u_{i,j}$ denotes the data sample at time index j and trace number i. For example, for an NMO velocity analysis, $u_{i,j} = u(h_i, t_0 + j\Delta t + v^2 h_i^2)$, where v denotes the velocity value to be tested at zero-offset time t_0 and h_i is the ith half-offset. The inner summation over i corresponds to N traces and the outer summation corresponds to a time window with length $2M + 1$ around the central point at $j = 0$. To determine the minimum semblance, we introduce a second time window with size $2K + 1$ in which the semblance values S_k are calculated according to

$$S_k = \frac{\sum\limits_{j=-M}^{M} \left(\sum\limits_{i=1}^{N} u_{i,k+j} \right)^2}{N \sum\limits_{j=-M}^{M} \left(\sum\limits_{i=1}^{N} u_{i,k+j}^2 \right)} \quad (k = -K, ..., K) \; . \tag{2}$$

We then define Minimum Semblance as the minimum value of this measure inside the outer time window, i.e.,

$$S_{min} = \min_{k=-K,\ldots,K} S_k . \tag{3}$$

This semblance value is then attributed to the time sample at the central point of the outer time window at $k = 0$.

A particular case is obtained when choosing the size of the inner window to be a single sample only, i.e., $M = 0$. This choice results in

$$S_k = \frac{\left(\sum\limits_{i=1}^{N} u_{i,k} \right)^2}{N \left(\sum\limits_{i=1}^{N} u_{i,k}^2 \right)} , \tag{4}$$

i.e., no inner window at all.

Procedure

We test minimum semblance for NMO velocity analysis in a CMP section. In this case, the coherence value is supposed to reflect how well the hyperbolic curve corresponding to the selected value of the stacking velocity fits the curve of the signal in the data. A good fit must produce a peak in the semblance section, while a bad fit must produce a significantly lower coherence value.

For minimum semblance, we compute the semblance measures S_k for an adequate time window size K. For instance, if $K = 1$ then we calculate semblance values S_{-1}, S_0 and S_1 for times $t_0 - \Delta t$, t_0 and $t_0 + \Delta t$, where Δt is the time sample. Once we have values S_k associated to all of these times, we select the minimum value to define the minimum semblance. For an appropriate size of the time window, we expect the semblance results not to be very different from each other for neighbouring traveltime samples. If the test curves fall inside a coherent event, the smallest value S_{min} is still expected to be relatively high. On the other hand, if the test curves fall outside a coherent event, at least one of the calculates values for S_j should be rather small, even if there is some random correlation between the traces. In this way, the

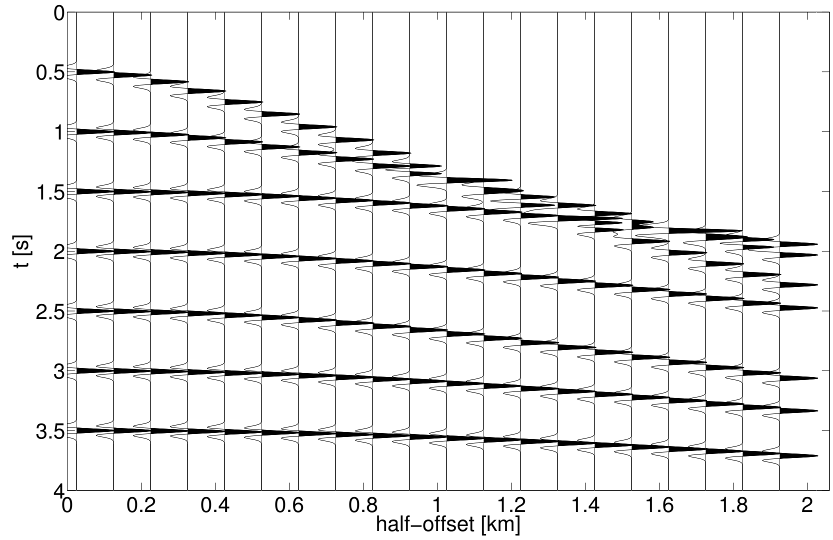

Figure 1: Noise-free synthetic CMP section.

minimization criterion is expected to lead to increased resolution as compared to conventional semblance, which would sum over such incidental correlations.

In contrast, choosing the maximum instead of the minimum value can be expected to do not much good for already high coherence values, but might strongly increase the coherence measure outside seismic events because of random correlations at some t_0.

The modification in the calculation of minimum semblance as compared to conventional semblance is rather small. For this reason, it has approximately the same computational cost. This is an advantage over Weighted and AB semblance, which present significantly higher computational costs. While this might not be relevant for a conventional velocity analysis, it can become a prohibitive factor in other applications of semblance analysis such as, e.g., the common-reflection-surface (CRS) method, which depends on several orders of magnitudes more semblance calculations.

NUMERICAL EXPERIMENTS

We tested the above minimum semblance numerically in applications to NMO velocity analysis. In the first tests, we compared the behaviour of minimum semblance to conventional semblance (Taner and Koehler, 1969), weighted semblance (Luo and Hale, 2012), and AB semblance (Sarkar et al., 2001). In the second set of tests, we investigated the behaviour of the semblance measures as a function of the widow size.

Semblance comparisons

We started by a comparison of the different variations of semblance on a synthetic CMP section. Then we applied the semblance functions to a field data set.

Synthetic Data Figure 1 shows a synthetic CMP section containing 7 exactly hyperbolic events corresponding to RMS velocities of 1.5, 2.0, 3.0, 2.5, 2.0, 2.5 and 3.0 km/s at zero-offset times t_0 of 0.5, 1.0, 1.5, 2.0, 2.5, 3.0 and 3.5 s, respectively. Time sampling is 4 ms. To these data with identical constant amplitudes for all events, we added random white noise at 40 % of the amplitude.

On these data, we performed a stacking-velocity analysis. The resulting velocity spectra obtained with conventional, weighted and minimum semblances are depicted in Figure 2. Note that all semblance spectra in this work are normalized to their peak values to allow for comparison.

In this test, we calculated the minimum semblance using equation 4, i.e., without an inner window. The outer window had the size of 5 samples, being the same size as the windows used in the conventional and

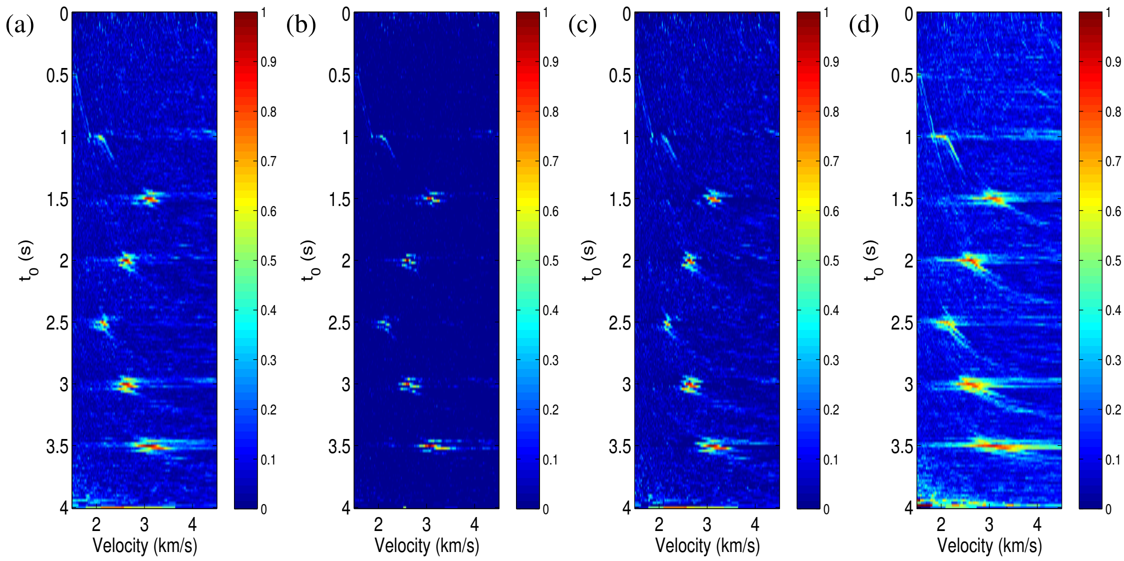

Figure 2: Velocity spectra with (a) Conventional, (b) Minimum, (c) Weighted, (d) AB Semblance.

weighted semblances. Color scale indicates the minimum value (blue) and the maximum value (red) of semblances. Semblance values vary between 0 and 1. Note that the minimum semblance section resolution increased compared to conventional, weighted and AB semblances. Minimum semblance provides a smaller number of red spots where there is high coherence than in the other spectra. This fact is favorable for picking the stacking velocity value.

Stacking velocities were extracted for the interpretable events from these velocity spectra. Figure 3a exhibits the absolute errors for these velocity values. We notice that the stacking velocity resulting from minimum semblance has the smallest error at six of the seven events. In some cases, it is equaled by other measures. Conventional measure produces the smallest error at three events, and it is equaled by minimum semblance at two events.

We can verify that all semblance measures provide mostly velocities that are acceptably close to the exact ones. Weighted semblance ($*$) produces a strong error for the event at $t_0 = 0.5$ s. AB Semblance (□) results in one slightly larger error for the event at $t_0 = 1.0$ s, which is probably due to the conflicting dips. All other velocities present significantly low error results, in other words, they are very close to the exact values.

Also, Figure 3b shows the velocity and normal-traveltime errors generating by picking the semblance maxima in the velocity spectra. Note that minimum semblance has null absolute error for traveltime position in six of the seven events.

Field Data For a more meaningful test, we repeated the above analysis for the field-data CMP section depicted in Figure 4. Sampling rate is again 4 ms. Figure 5 shows the velocity spectra obtained with conventional, minimum, weighted and AB semblances. We used again no inner window for the minimum-semblance computations. The outer window was one sample to each side, the same as for the other measures.

To study the effectiveness of the semblance functions for real data, we applied an NMO correction to the CMP section using the picked velocities obtained by each measure. The best flattening among the functions should indicate which one produces the velocities that best describe coherent events in this CMP data set. Note that in this test, we picked simply the velocities with the highest semblances, without regard as to whether they belong to primary, multiple, or accidentally correlated events. The NMO-corrected sections with the picked stacking velocities obtained with conventional, minimum, weighted and AB semblances are shown in Figure 6. We notice that overall, AB and minimum-semblance results provide better event flattening than those from conventional and weighted semblances. This can be best seen for the event at 2.5 s. Between these two semblance measures that produce comparable results, minimum semblance has

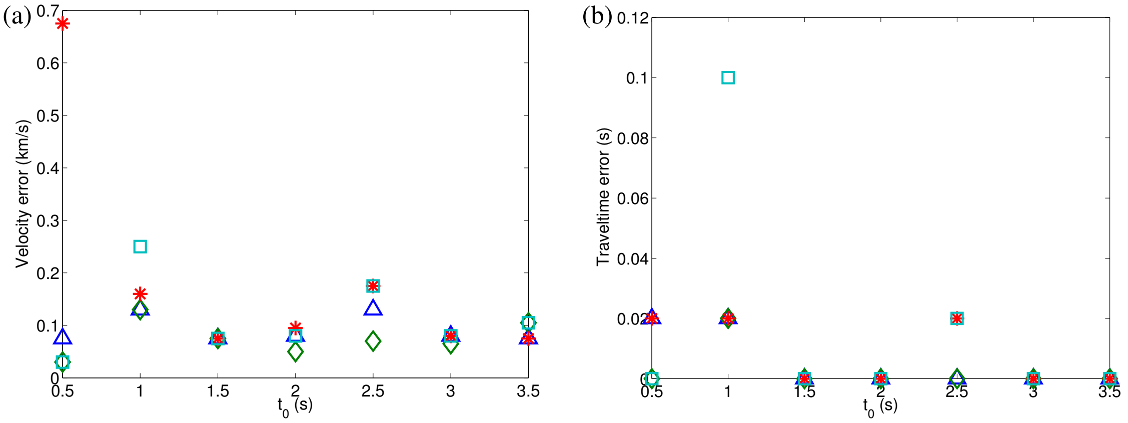

Figure 3: Parameter error from picking the semblance maxima in Figure 2 using conventional (△), minimum (◇), weighted (∗) and AB (□) semblance. (a) Absolute velocity error. (b) Absolute traveltime error.

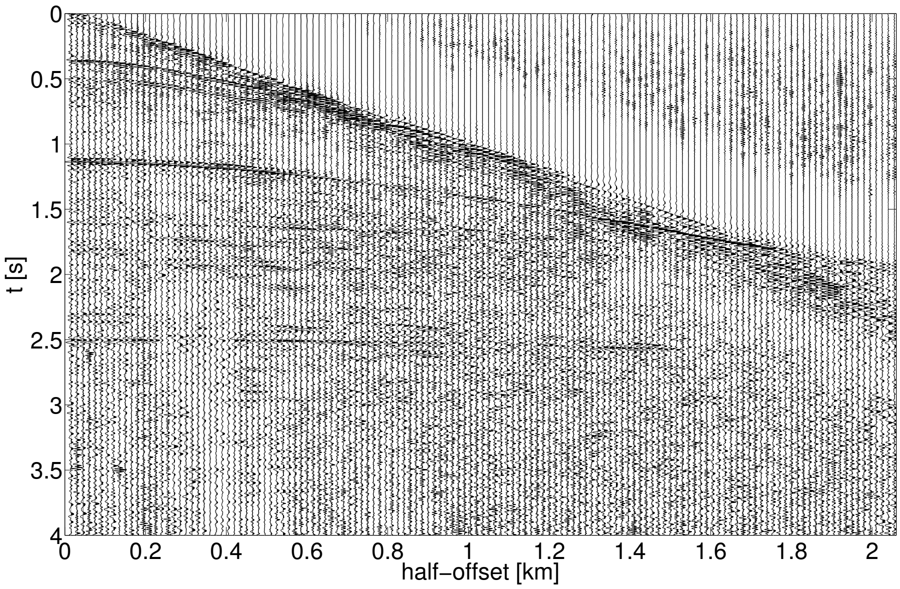

Figure 4: CMP section for field data.

lower computacional cost than AB semblance.

Window-size dependence

In the next series of tests, we studied the behaviour of minimum semblance as a function of the size of the two windows it uses. We start with the dependence on the outer window. Note that while we kept the noise the same for the comparison of the different semblance measures with a given window size, we replaced it with another realization when changing the window size in order to obtain a statistically more meaningful result.

Outer window We observed an increase in the resolution of minimum-semblance sections as compared to conventional semblance regardless of the selected time-window size. Tests indicate that conventional semblance loses resolution as the window size increases. The same does not happen with minimum semblance, the results of which were much less dependent on the window size. It retains its resolution even for rather large time windows, which makes the choice of the window size less important than for conventional

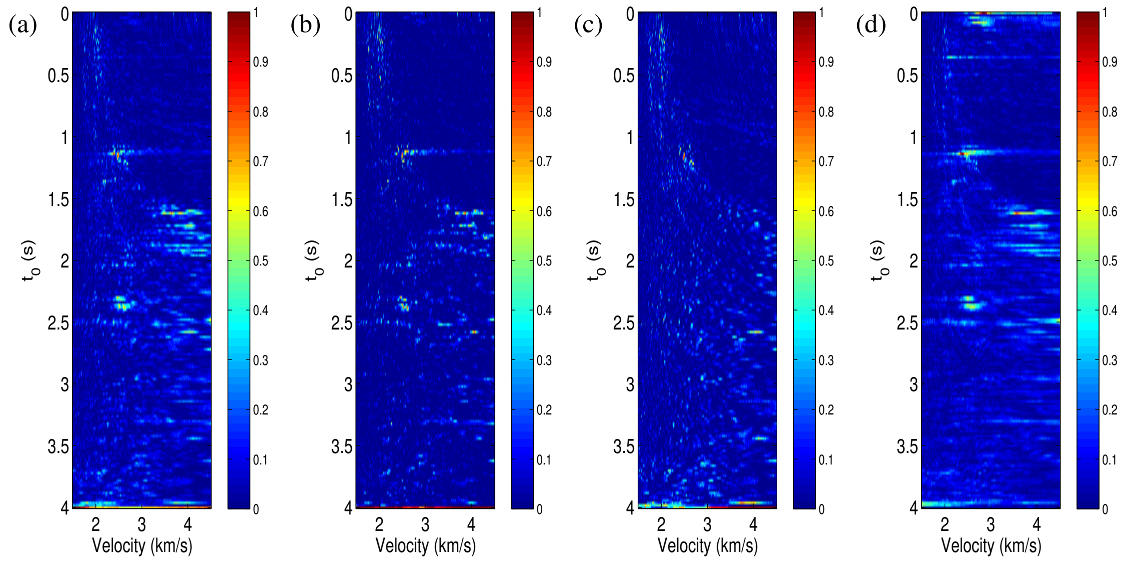

Figure 5: Velocity spectra of the real data obtained with (a) conventional, (b) minimum, (c) weighted and (d) AB semblance.

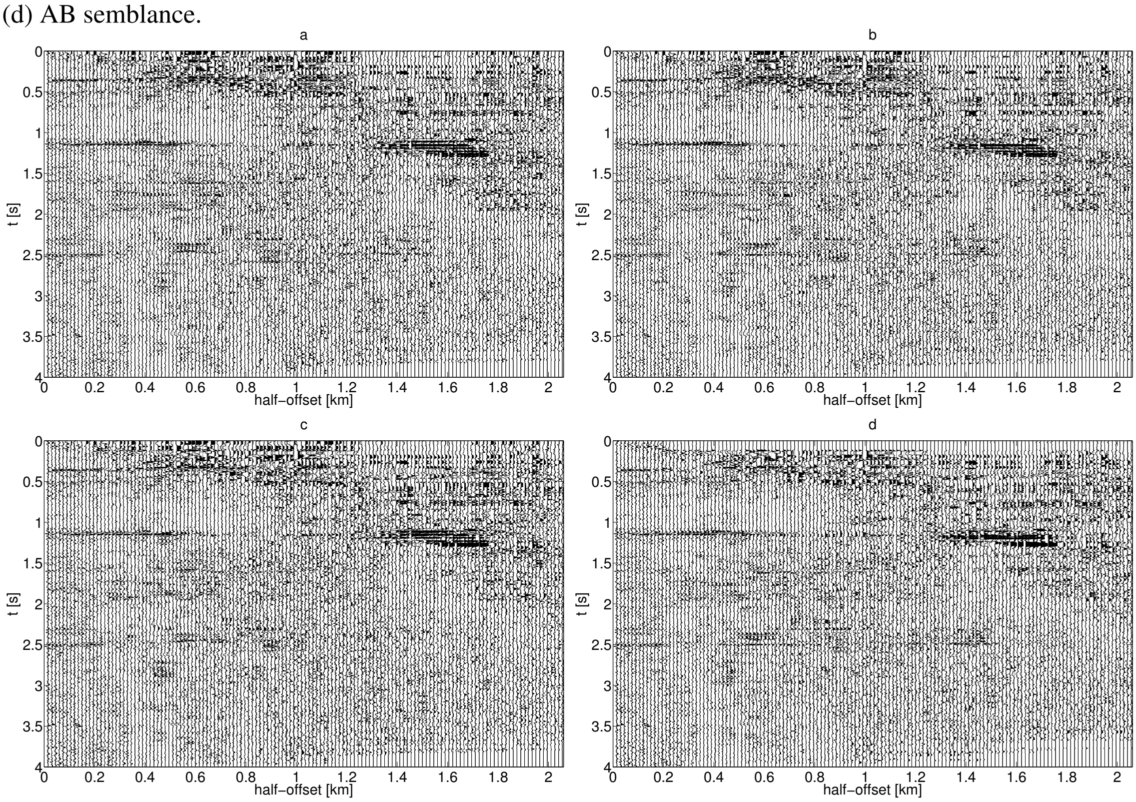

Figure 6: NMO correction applied to CMP section for velocities obtained by (a) conventional semblance, (b) minimum semblance, (c) weighted semblance and (d) AB semblance.

semblance.

Figures 7, 8 and 9 show that conventional, weighted and AB semblance sections lose resolution with increasing window size. In contrast, minimum semblance preserves its resolution behaviour for a large range of window sizes. Note that the smallest time window used for the spectra in Figure 7 has size of 3 samples (1 to each side) and the largest time window for Figure 9 has size 21 (10 to each side).

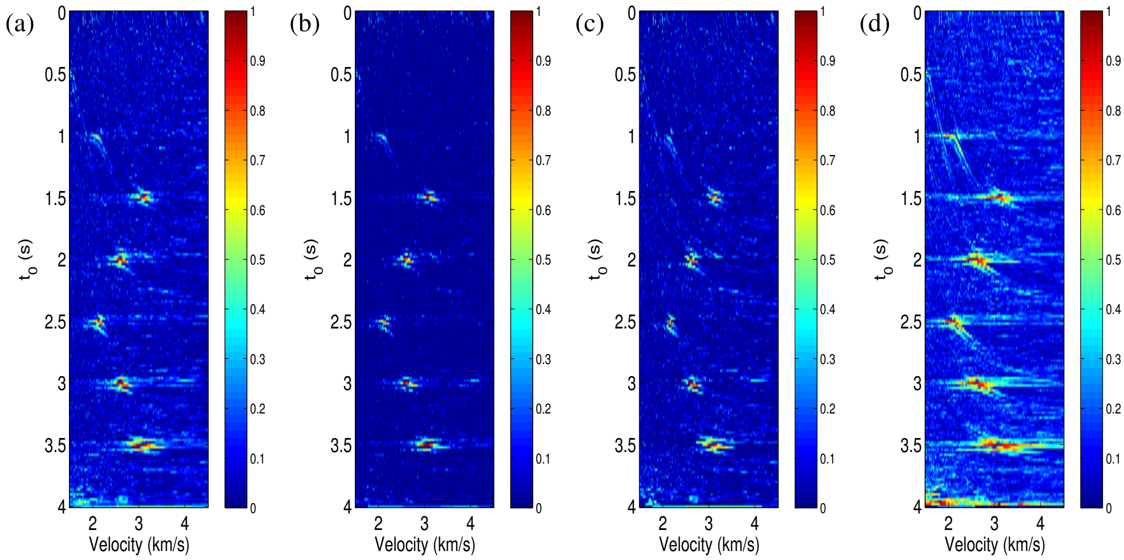

Figure 7: Velocity spectra for window size 3. (a) Conventional, (b) minimum, (c) weighted, (d) AB semblance.

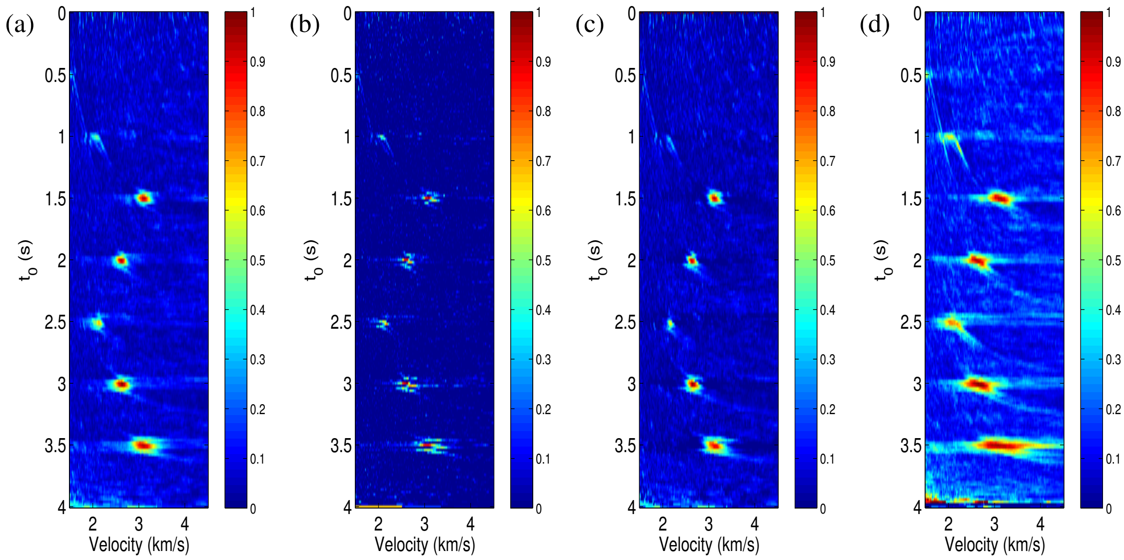

Figure 8: Velocity spectra for window size 11. (a) Conventional, (b) minimum, (c) weighted, (d) AB semblance.

High resolution of semblance sections is desirable because the picking process becomes an easier step of seismic processing and the selected velocities can be expected to remain more precise even in the presence of high noise levels. Picking wrong velocity at this stage may result in incorrected migration and consequently require additional effort in subsequent migration velocity analysis. Thus, if the window size affects the resolution of the semblance spectra analyzed, there is a danger of chosing an inadequate time window. This danger is reduced with minimum semblance.

However, an increased resolution might favor a bias in the selected velocities, if the position of the semblance peak is incorrect. To investigate whether minimum semblance is subject to this kind of velocity error, we extracted the velocities at the semblance peaks in the spectra of Figures 7, 8, and 9. Figures 10, 11, and 12 show that the minimum-semblance velocities are very close to the real values of velocities of the synthetic data example. While the velocity errors increase with window size for conventional, weighted and AB semblance, the velocities extracted from the minimum-semblance spectra remain of the same quality. This shows again that velocity-spectra using minimum-semblance are less dependent on the size

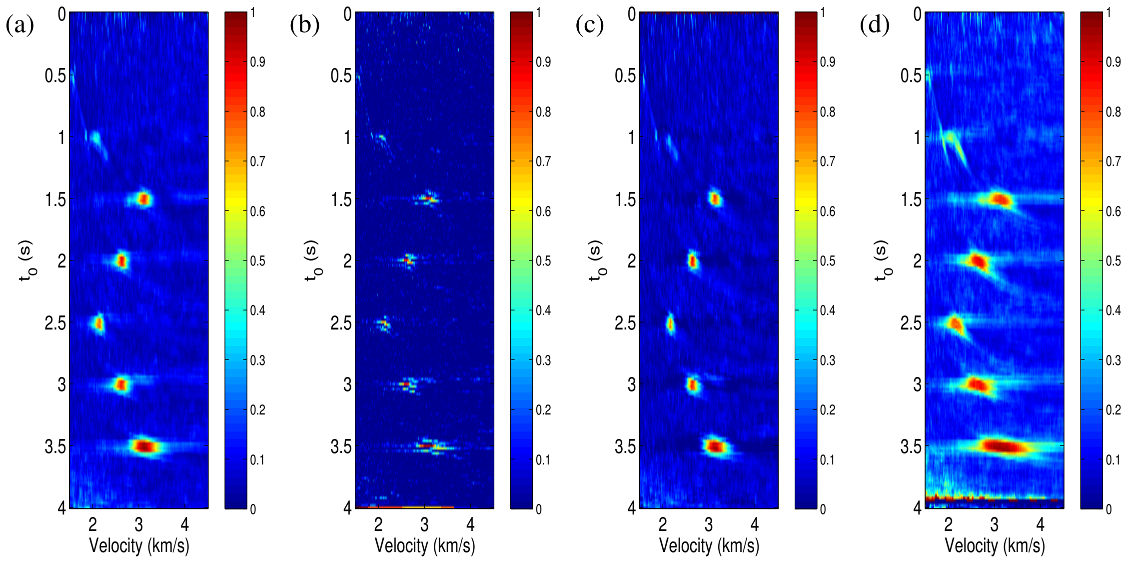

Figure 9: Velocity spectra for window size 21. (a) Conventional, (b) minimum, (c) weighted, (d) AB semblance.

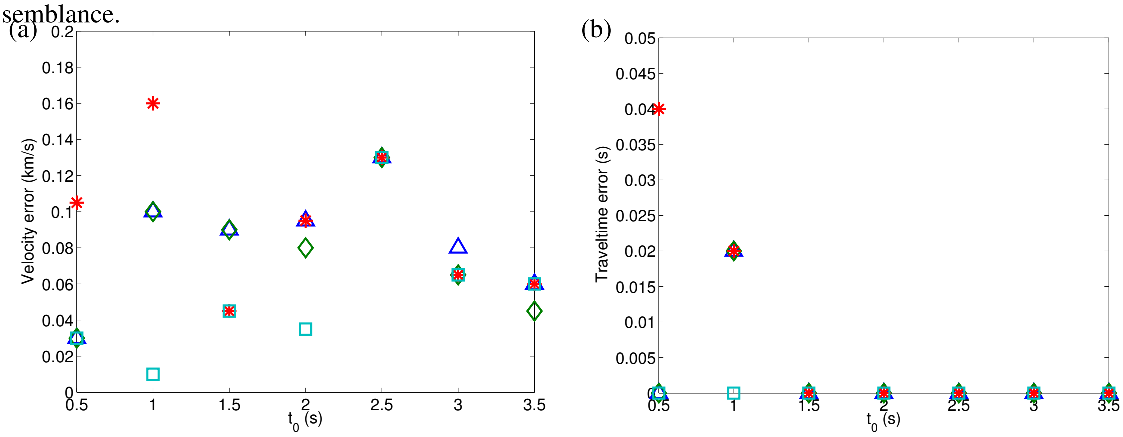

Figure 10: Parameter error from picking the semblance maxima in Figure 7 using a time window of 3 samples in conventional (△), minimum (◊), weighted (∗) and AB (□) semblance. (a) Absolute velocity error. (b) Absolute traveltime error.

of the chosen window than using other semblances. Therefore, the optimal window size can be adequately chosen with respect to the noise present in the data, without having to worry about bad velocity picks because of too large or too small windows.

Inner window The last series of tests regards the size of the inner window in the minimum-semblance calculation. Figures 13 to 16 compare the resulting minimum-semblance velocity spectra for a number of different window sizes. Also shown for comparison are the corresponding velocity spectra for conventional semblance and minimum semblance with no inner window. For the latter, the window size is the same as of the outer minimum-semblance window, being 5 samples in Figure 13, 9 samples in Figure 14, 21 samples in Figure 15, and 41 samples in Figure 16.

In the sequence of Figures 13 to 16, we see that minimum semblance without an inner window provides the sharpest peaks, but that the peaks almost vanish for larger windows. The inner window helps to preserve the peaks while still improving resolution over conventional semblance. A choice of an inner window half the size of the outer window seems a good compromize between computation cost and resolution without loss of information.

The quality of the parameter extraction as a function of the window size is evaluated in the next set of tests. Figures 17 to 20 show the velocity and normal-traveltime errors generating by picking the semblance

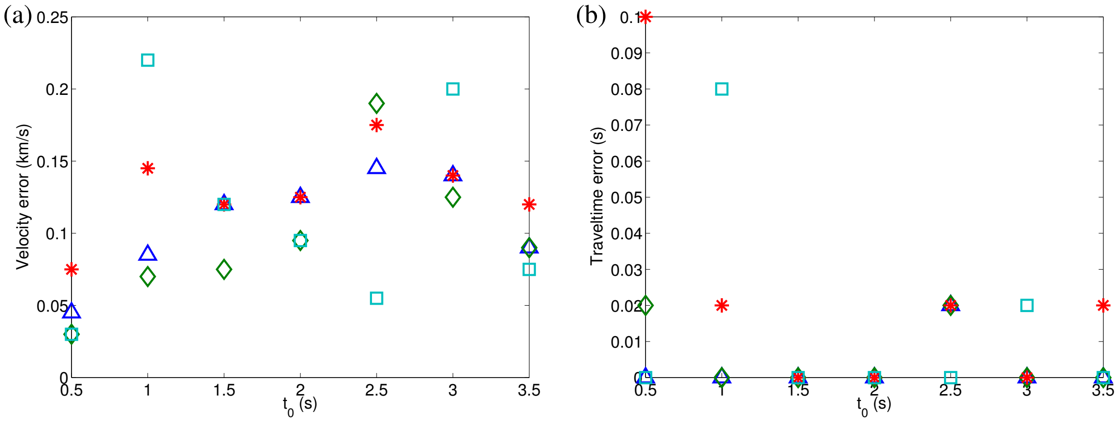

Figure 11: Parameter error from picking the semblance maxima in Figure 8 using a time window of 3 samples in conventional (△), minimum (◊), weighted (∗) and AB (□) semblance. (a) Absolute velocity error. (b) Absolute traveltime error.

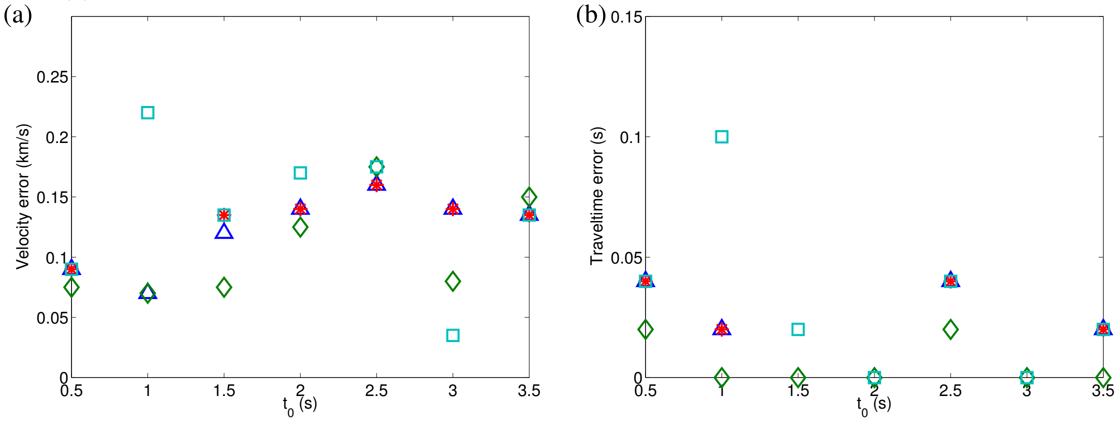

Figure 12: Parameter error from picking the semblance maxima in Figure 9 using a time window of 3 samples in conventional (△), minimum (◊), weighted (∗) and AB (□) semblance. (a) Absolute velocity error. (b) Absolute traveltime error.

maxima in the above velocity spectra.

We recognize that the velocities are extracted with similar precision at a comparable error for all semblance measures, with possibly a slight advantage for the minimum semblance with an inner window of half to full size of the outer window. For short lengths of the outer window, minimum semblance without an inner window also provided rather accurate velocity estimates. It is to be noted that the computational cost of minimum semblance with a nonzero inner window increases over conventional semblance.

Field data We repeated these tests for the field data of Figure 4. In this case, we compared the performance of minimum semblance with different outer window sizes from 5 to 21 samples and inner window sizes from 3 samples to full outer window size. Figures 21 to 26 depict the resulting velocity spectra, comparing the best results obtained with minimum semblance to those of conventional semblance. Note that minimum semblance yields higher resolution in the corresponding spectra, and the visualization of the velocity trend on the semblance panel is somewhat better than the conventional approach when choosing an inner window about half the size of the outer window or slightly larger. The velocity trend is probably best recognizable in Figure 22b, which was obtained with an outer window of 7 samples and an inner one of 5 samples, in Figure 23b with outer window of 9 samples and inner one of 5 samples, or in Figure 24c with outer window of 11 samples and inner one of 7 samples. For larger inner windows, the minimum-semblance spectra start to show the same out-of-focus aspect as the conventional-semblance specta, and for larger outer windows, the quality of the velocity spectra begin to deteriorate.

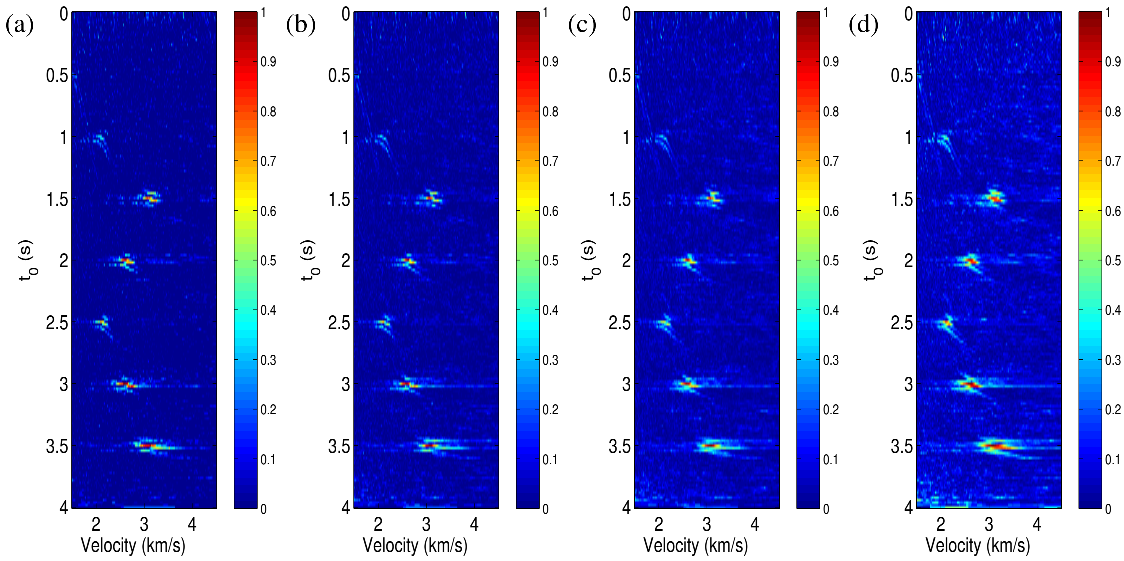

Figure 13: Velocity spectra with minimum semblance using an outer window of 5 samples (2 to each side), with inner window size (a) 1, (b) 3, and (c) 5 samples. (d) Conventional semblance.

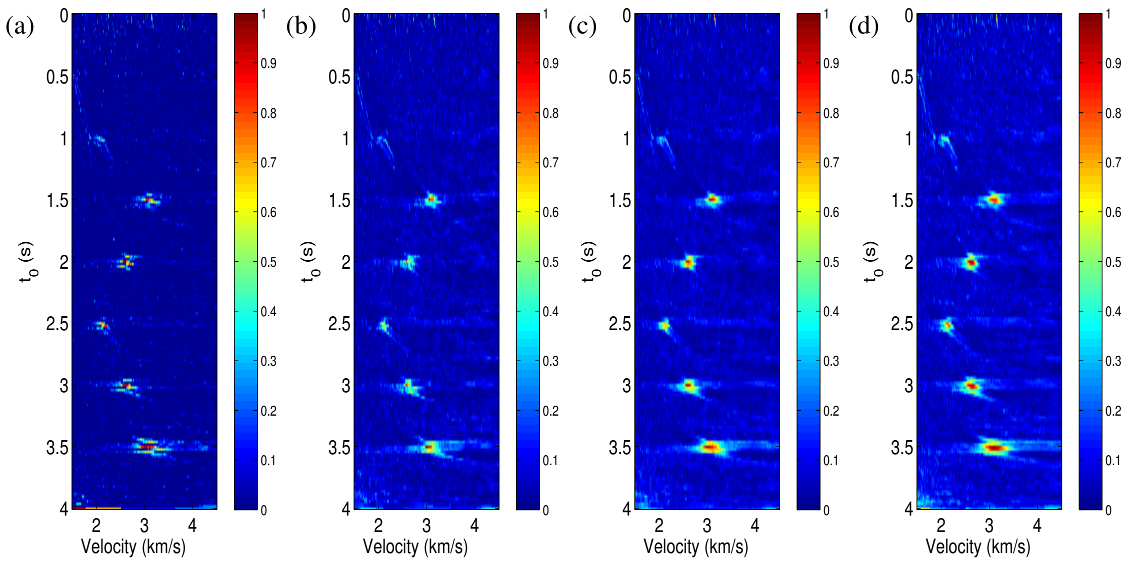

Figure 14: Velocity spectra with minimum semblance using an outer window of 9 samples (4 to each side), with inner window size (a) 1, (b) 5, and (c) 9 samples. (d) Conventional semblance.

CONCLUSIONS

Minimum semblance introduced in this work is a similar coherence measure to conventional semblance. Its idea is to select the minimum conventional-semblance value within a certain time window instead of determining a kind of average over these curves as for conventional semblance. If used without an inner window, minimum semblance has the same computational cost as conventional semblance. An inner window can be used to stabilize results, but adds to the computational cost.

In our numerical tests for stacking-velocity analysis in synthetic and real CMP sections, minimum semblance provided better resolution in the velocity spectra and allowed in many cases to pick superior velocity values. This improved resolution, which is practically independent of the time-window size, is an important advantage over other measures like conventional, weighted and AB semblances, which strongly

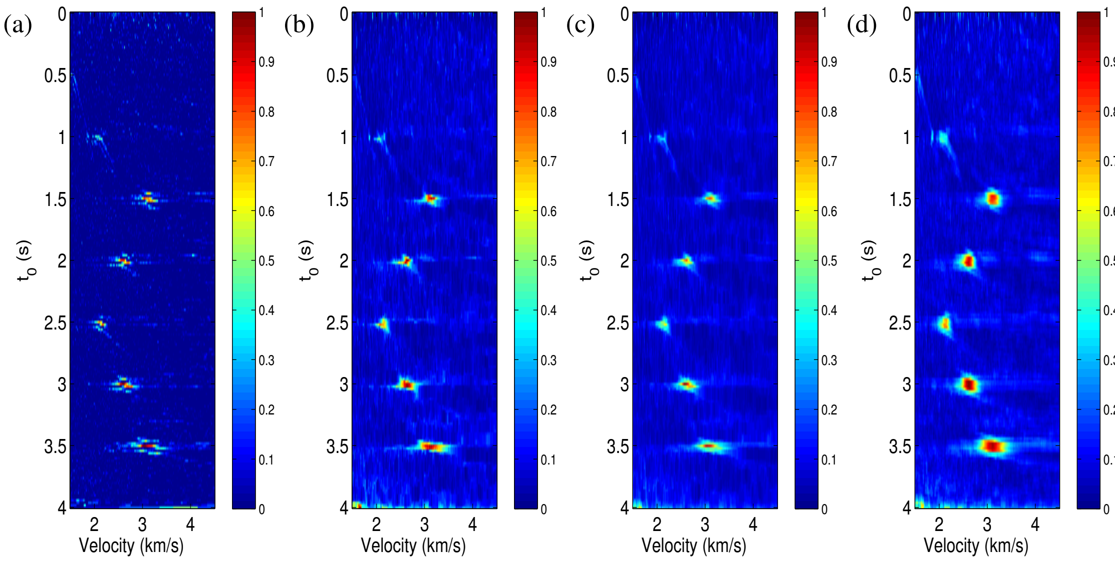

Figure 15: Velocity spectra with minimum semblance using an outer window of 21 samples (10 to each side), with inner window size (a) 1, (b) 11, and (c) 21 samples. (d) Conventional semblance.

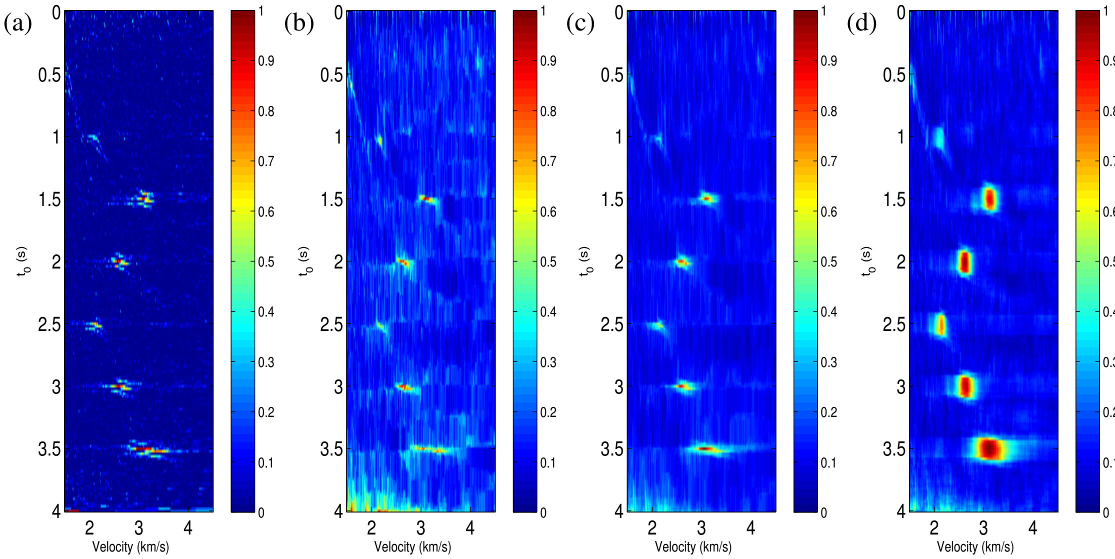

Figure 16: Velocity spectra with minimum semblance using an outer window of 41 samples (20 to each side), with inner window size (a) 1, (b) 21, and (c) 41 samples. (d) Conventional semblance.

depend on the choice of the window size.

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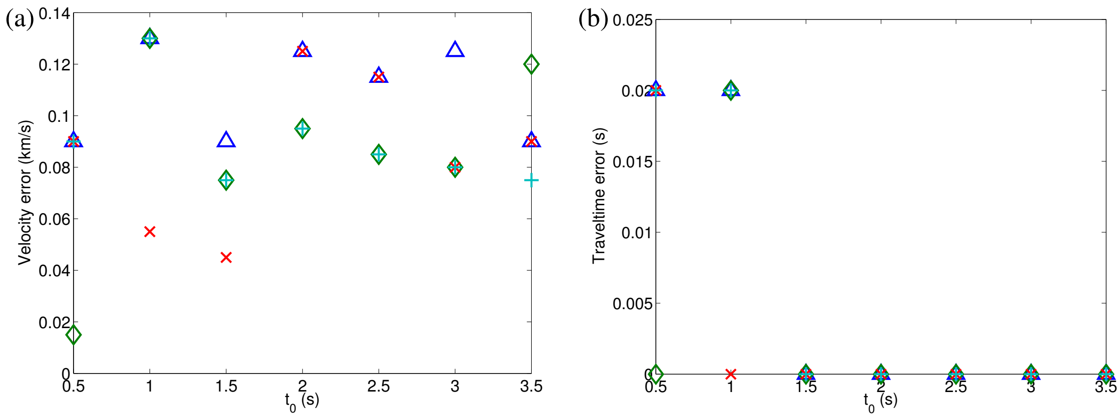

Figure 17: Parameter error from picking the semblance maxima in Figure 13 using an outer window of 5 samples in conventional semblance (△) and minimum semblance without inner window (◊) and with inner windows of 3 (×) and 5 samples (+). (a) Absolute velocity error. (b) Absolute traveltime error.

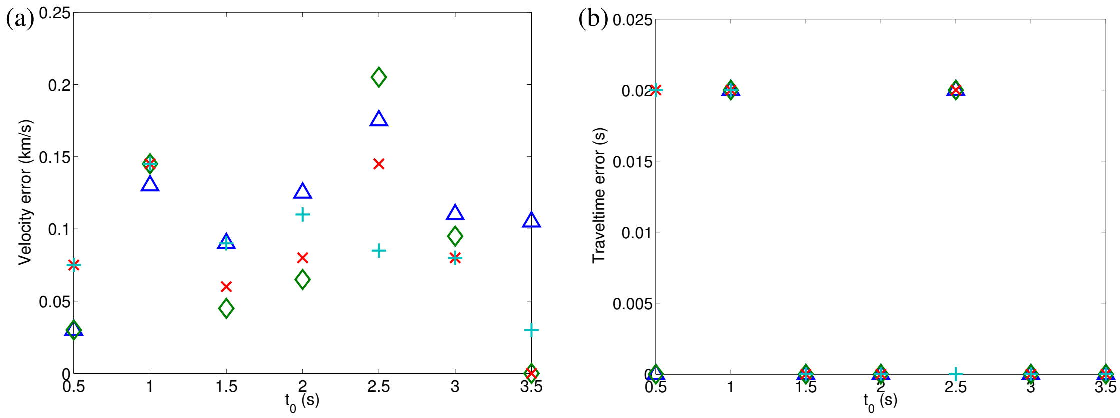

Figure 18: Parameter error from picking the semblance maxima in Figure 14 using an outer window of 9 samples in conventional semblance (△) and minimum semblance without inner window (◊) and with inner windows of 5 (×) and 9 samples (+). (a) Absolute velocity error. (b) Absolute traveltime error.

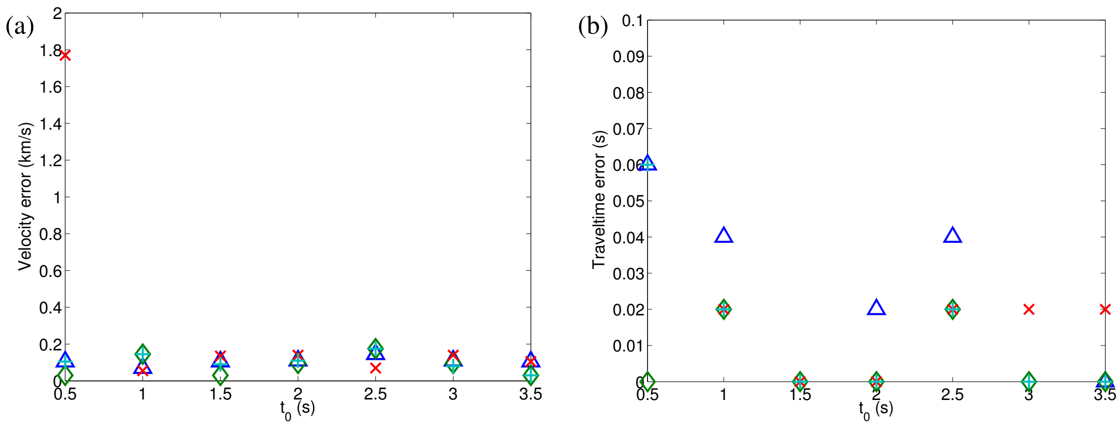

Figure 19: Parameter error from picking the semblance maxima in Figure 15 using an outer window of 21 samples in conventional semblance (△) and minimum semblance without inner window (◊) and with inner windows of 11 (×) and 21 samples (+). (a) Absolute velocity error. (b) Absolute traveltime error.

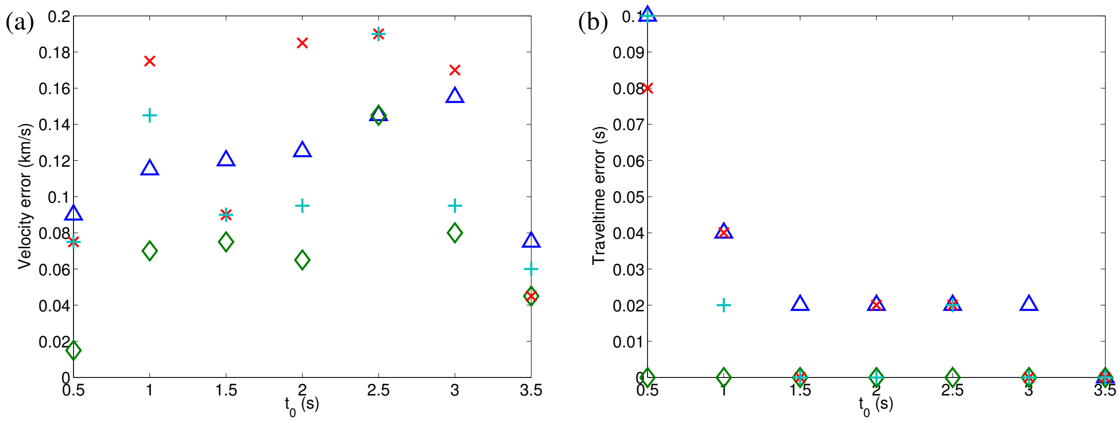

Figure 20: Parameter error from picking the semblance maxima in Figure 16 using an outer window of 41 samples in conventional semblance (△) and minimum semblance without inner window (◇) and with inner windows of 21 (×) and 41 samples (+). (a) Absolute velocity error. (b) Absolute traveltime error.

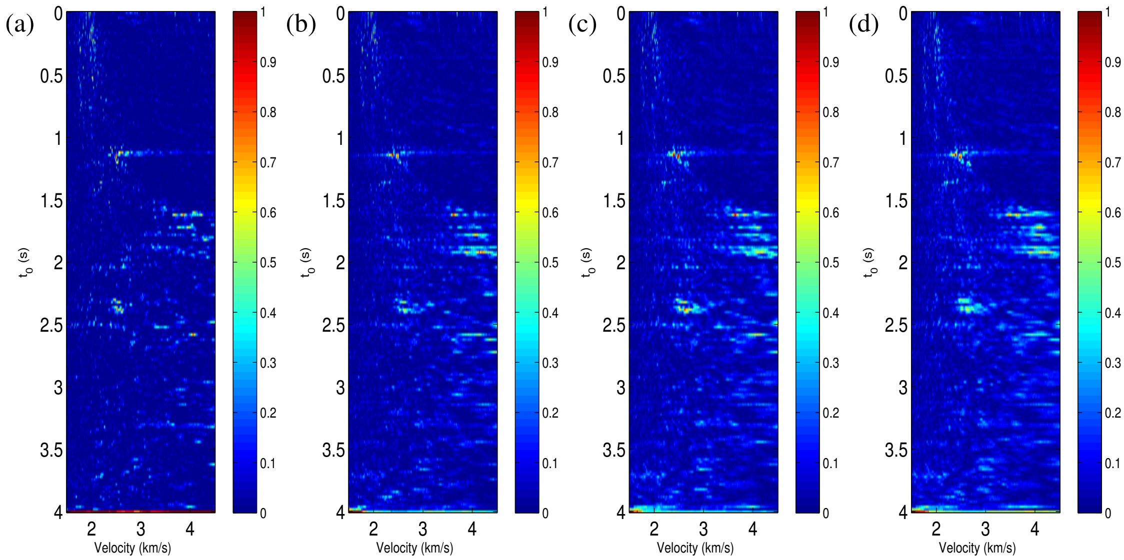

Figure 21: Real data: Velocity spectra with minimum semblance using an outer window of 5 samples (2 to each side), with inner window size (a) 1, (b) 3, and (c) 5 samples. (d) Conventional semblance.

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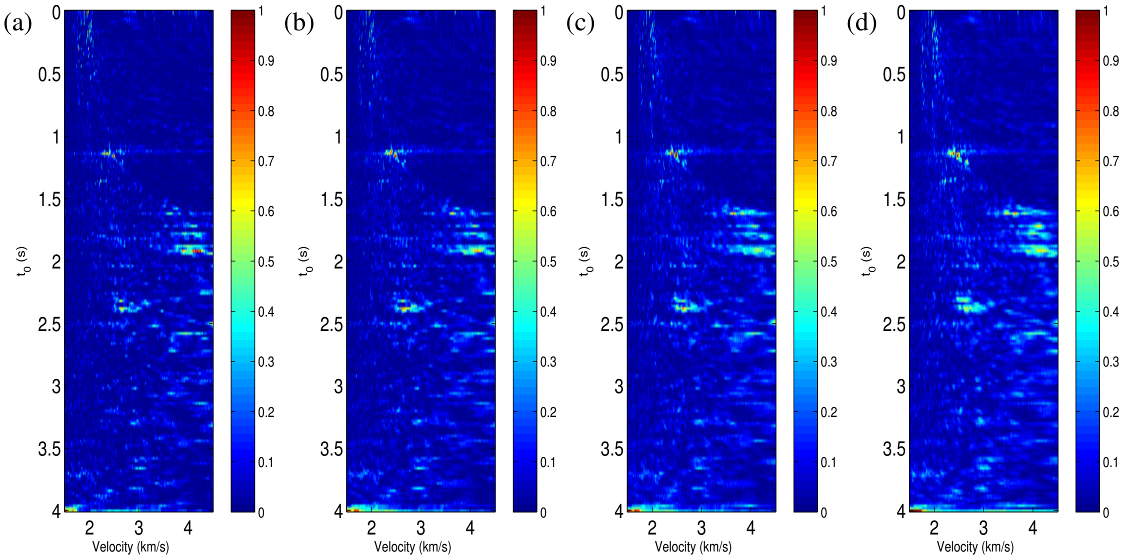

Figure 22: Real data: Velocity spectra with minimum semblance using an outer window of 7 samples (3 to each side), with inner window size (a) 3, (b) 5, and (c) 7 samples. (d) Conventional semblance.

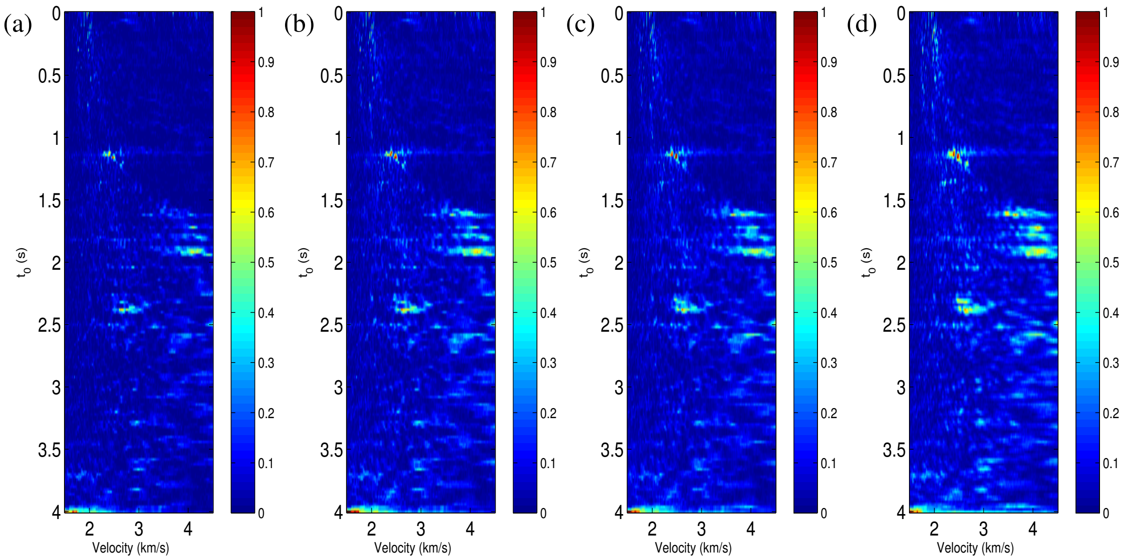

Figure 23: Real data: Velocity spectra with minimum semblance using an outer window of 9 samples (4 to each side), with inner window size (a) 5, (b) 7, and (c) 9 samples. (d) Conventional semblance.

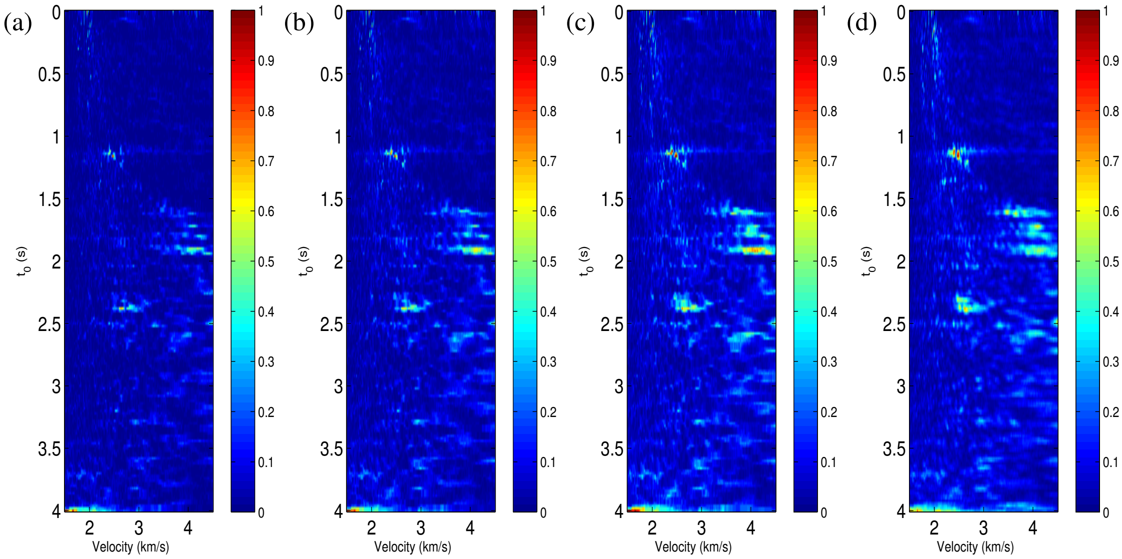

Figure 24: Real data: Velocity spectra with minimum semblance using an outer window of 11 samples (5 to each side), with inner window size (a) 5, (b) 7, and (c) 9 samples. (d) Conventional semblance.

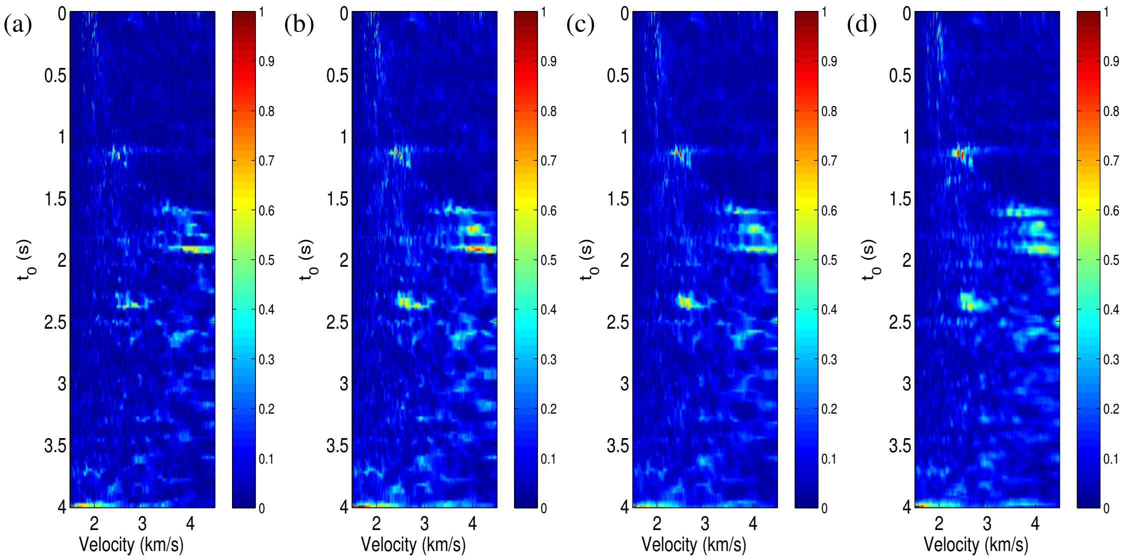

Figure 25: Real data: Velocity spectra with minimum semblance using an outer window of 15 samples (7 to each side), with inner window size (a) 5, (b) 9, and (c) 15 samples. (d) Conventional semblance.

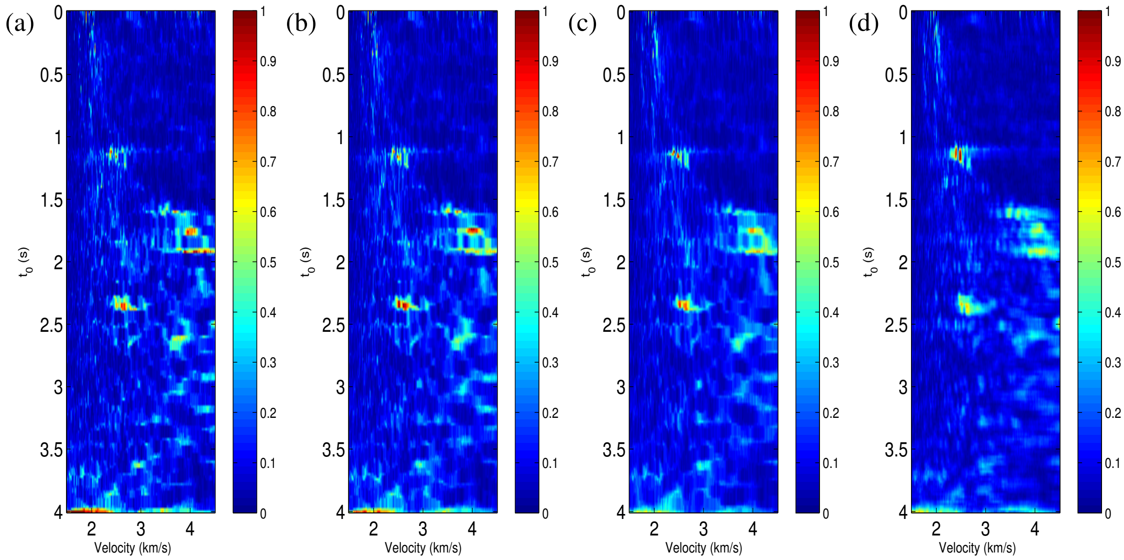

Figure 26: Real data: Velocity spectra with minimum semblance using an outer window of 21 samples (10 to each side), with inner window size (a) 9, (b) 13, and (c) 19 samples. (d) Conventional semblance.