Minimum semblance: A new coherence measure to improve resolution of semblance sections

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This paper was prepared for presentation at the 14^{th} International Congress of the Brazilian Geophysical Society, held in Rio de Janeiro, Brazil, August 3-6, 2015.

Abstract

In this work, we introduce Minimum Semblance as an alternative method to calculate the coherence of seismic events. Minimum semblance is a small modification of conventional semblance, the purpose of which is to increase the resolution of semblance sections. The idea is to utilize the time window used in conventional semblance to find the minimum semblance value of all parallel curves instead of summing in time. 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.

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) given by

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

where $u_{i,j}$ denotes the data sample at time index j and trace number i. The inner summation over i corresponds to N traces and the outer summation corresponds to a time window with length $2M+1$. To introduce the minimum semblance, we disregard the time window $(M = 0)$, resulting in

$$S_j = \frac{\left(\sum_{i=1}^{N} u_{i,j} \right)^2}{N \left(\sum_{i=1}^{N} u_{i,j}^2 \right)}. \tag{2}$$

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

$$S_{min} = \min\{S_j,\ j = 1, \ldots, 2M+1\}. \tag{3}$$

Procedure

For velocity analysis in a CMP section, 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 produces significantly lower coherence values.

For the Minimum Semblance, we compute the semblance measure S_j for an adequate time window M. For instance, if $M = 1$ then we calculate semblance values S_{-1}, S_0 and S_1 for times $t_0 - dt, t_0$ and $t_0 + dt$, where dt is the time sample. Once we have values S_j associated to all of these times, we select the minimum value to define the Minimum Semblance. For an appropriate size of time window, the semblance results will not 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 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 of 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.

To evaluate the behaviour of Minimum Semblance, we compared CMP velocity analysis results to those obtained with other semblance approaches.

Numerical experiments

Our first numerical tests consisted of a synthetic CMP section. Then we applied the semblance functions to a field data set.

Synthetic Data

Figure 1 shows a synthetic CMP section generated from a model using RMS velocities of 1.5, 2.0, 3.0, 2.5, 2.0, 2.5 and 3.0 km/s and times t_0 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 constant event amplitudes, we added random white noise at 40 % of the maximum amplitude.

On these data, we performed a stacking-velocity analysis. The resulting velocity spectra obtained with conventional, weighted and minimum semblances with a window size of 5 samples are depicted in Figure 2. 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 and weighted 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. AB semblance is not exhibited because its results are almost indistinguishable from the conventional ones in this case, where the events do not present amplitude variations.

We extracted the stacking velocities for the interpretable events from these velocity spectra. Figure 3 exhibits the extracted velocities and compares them to the exact velocities (black $\circ$) for this example. We can verify that all semblance provide mostly velocities that are acceptably close to the exact ones. Weighted semblance (blue $*$) produces a strong error for the event at $t_0 = 0.5$ s. Minimum Semblance (red $\times$) results in one slightly larger error for the event at $t_0 = 1.5$ s, which is probably due to the conflicting dips. All other velocities almost cover the black circles that indicate the exact ones.

For a more detailed analysis, we have calculated the absolute errors for these velocity values (see Figure 4). We notice that the stacking velocity resulting from minimum semblance has the smallest error at five of the seven events. Conventional semblance produces the smallest error at two events, one of which is equaled by weighted semblance.

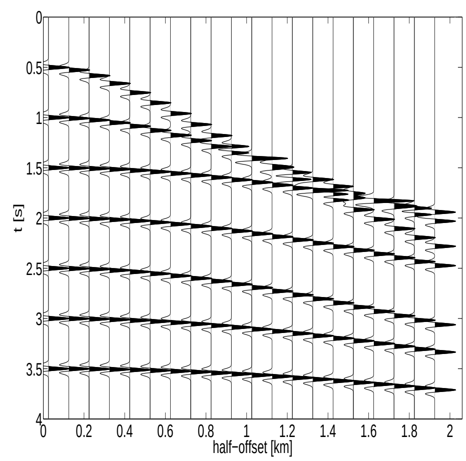

Figure 1: Noise-free synthetic CMP section.

Field Data

Figure 5 is a field-data CMP section with 4 ms time sampling. Figures 6 show the velocity spectra obtained with conventional, minimum, weighted and AB semblances, respectively, with a window size of one sample. To study the effectiveness of the functions in 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 will indicate which one is the best for this set of CMP data. The NMO-corrected sections with the picked stacking velocities obtained with conventional, minimum, weighted and AB semblances are shown in Figure 7. Notice that for the event at time 2.5 s, AB and Minimum-Semblance results provide better event flattening than those from conventional and weighted semblances. Although the results are comparable, minimum semblance has lower computacional cost than AB semblance.

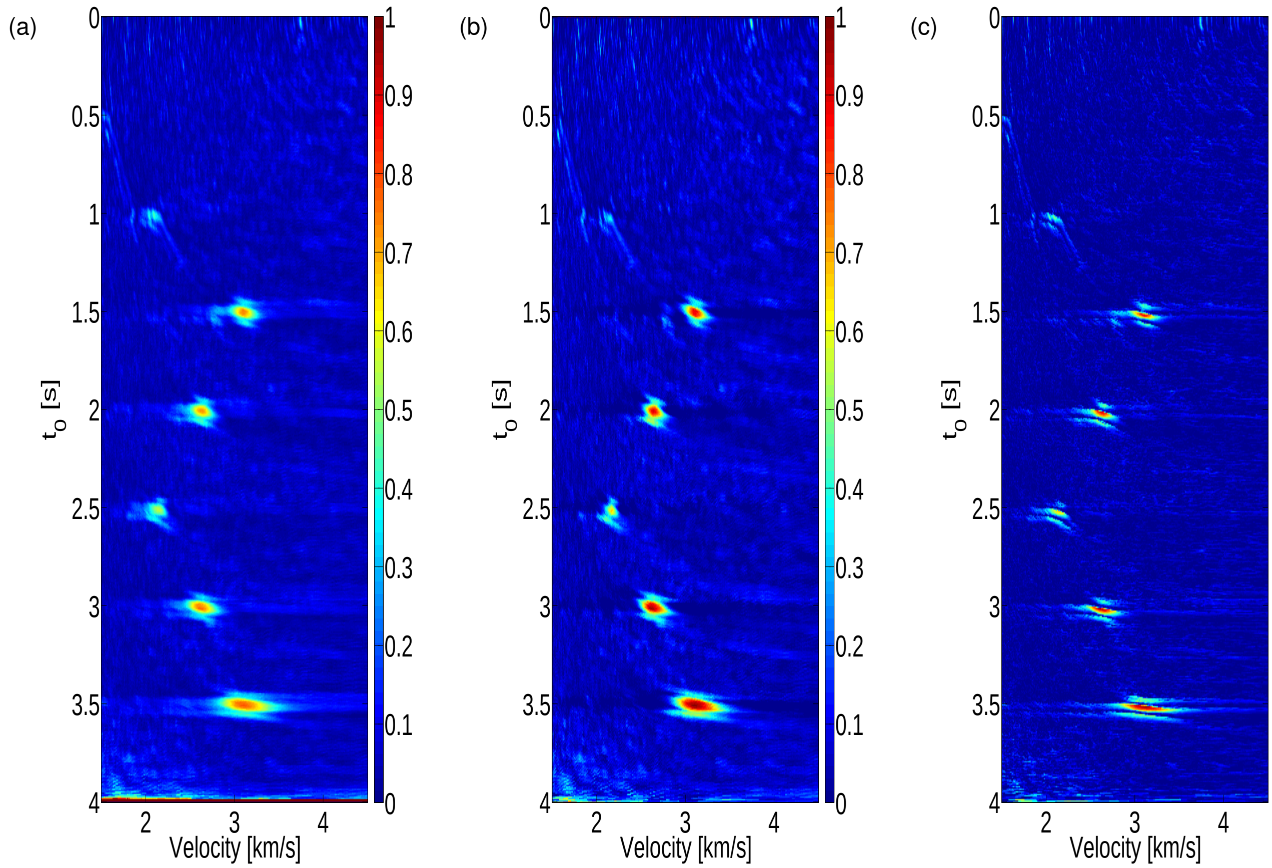

Figure 2: Velocity spectra with (a) Conventional, (b) Weighted, (c) Minimum Semblance.

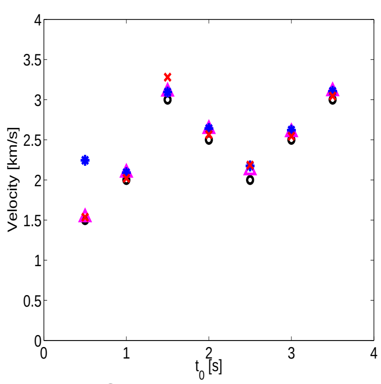

Figure 3: Picked RMS velocities for conventional (magenta △), weighted (blue $*$), and minimum (red $\times$) semblances, and comparison with the exact values (black $\circ$).

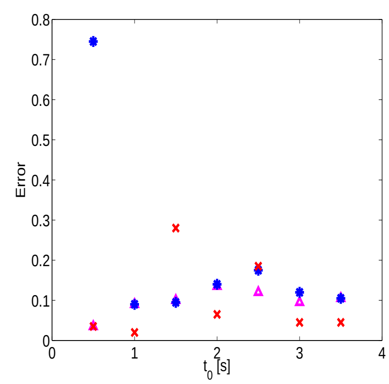

Figure 4: Absolute velocity error for conventional (magenta △), weighted (blue $*$), and minimum (red $\times$) semblances in deviation from the exact values.

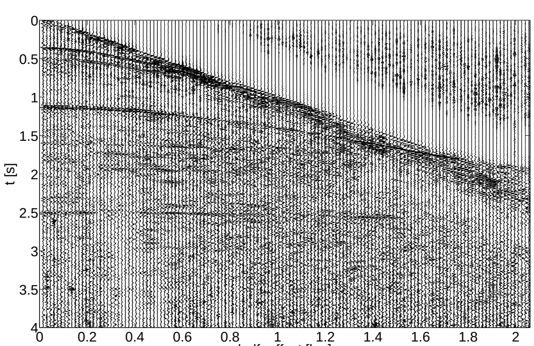

Figure 5: CMP section for field data.

Conclusions

The Minimum Semblance introduced in this work is a similar coherence measure to conventional semblance. The time window is used to find the minimum semblance value along all parallel curves instead of determining a kind of average over these curves. It has the same computational cost as conventional semblance. In our numerical tests for stacking-velocity analysis in synthetic and real CMP sections, it provided better resolution in the velocity spectra and allowed in many cases to pick superior velocity values.

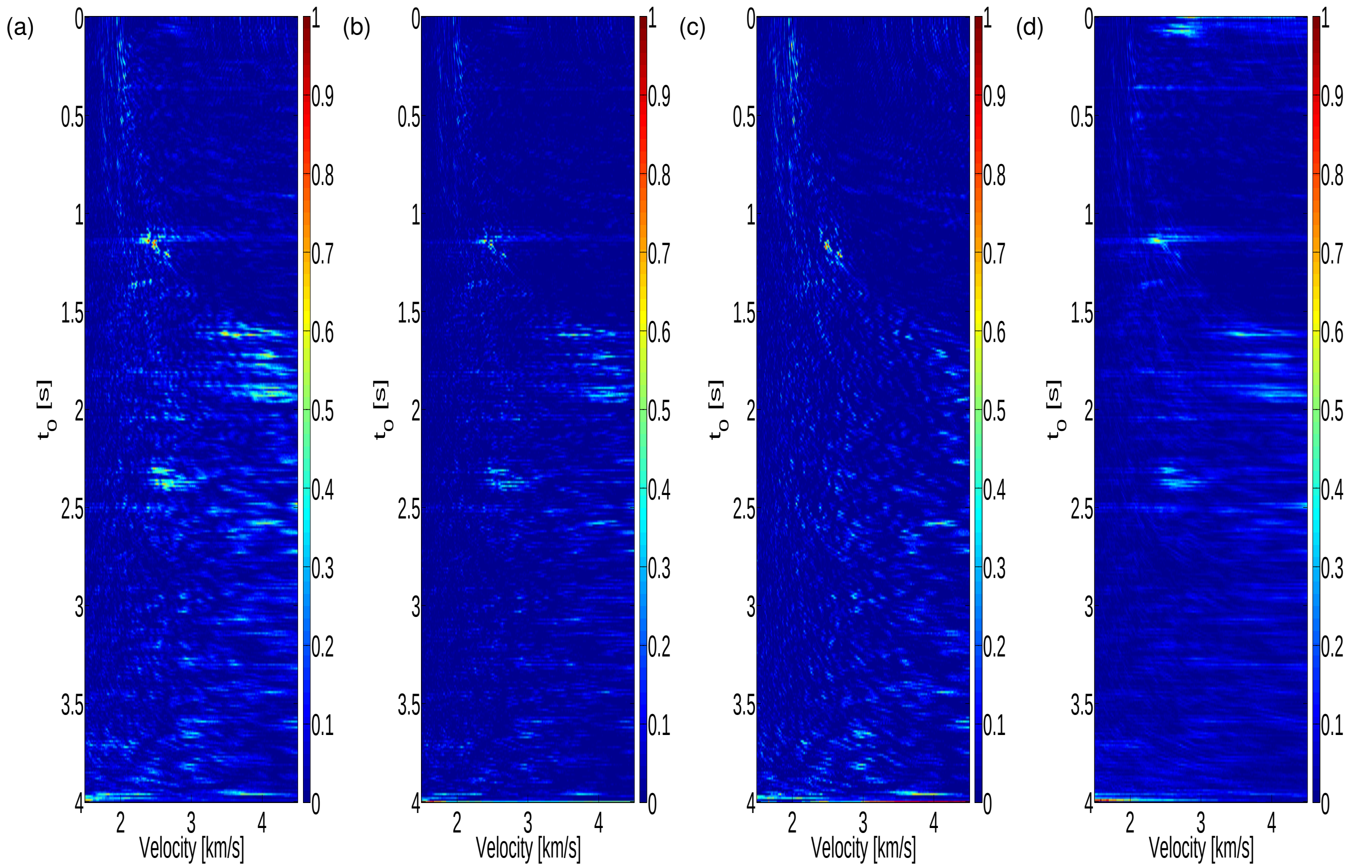

Figure 6: Velocity spectra of the real data obtained with (a) conventional, (b) minimum, (c) weighted and (d) AB semblance.

Acknowledgments

We thank PRH-PB, ANP, CNPq, Petrobras and the sponsors of the WIT consortium for financial support.

References

Douze, E. J. and Laster, J. (1979). Statistics of semblance. *Geophysics*, 44(12):1999–2003.

Fomel, S. (2009). Velocity analysis using AB semblance. *Geophysical Prospecting*, 57(3):311–321.

Luo, S. and Hale, D. (2012). Velocity analysis using weighted semblance. *Geophysics*, 77(2):U15–U22.

Sarkar, D., Baumel, R., and Larner, K. (2002). Velocity analysis in the presence of amplitude variation. *Geophysics*, 67(5):1664–1672.

Sarkar, D., Castagna, J. P., and J., L. W. (2001). AVO and velocity analysis. *Geophysics*, 66(4):1284–1293.

Taner, M. T. and Koehler, F. (1969). Velocity spectra - digital computer derivation and applications of velocity functions. *Geophysics*, 34(6):859–81.

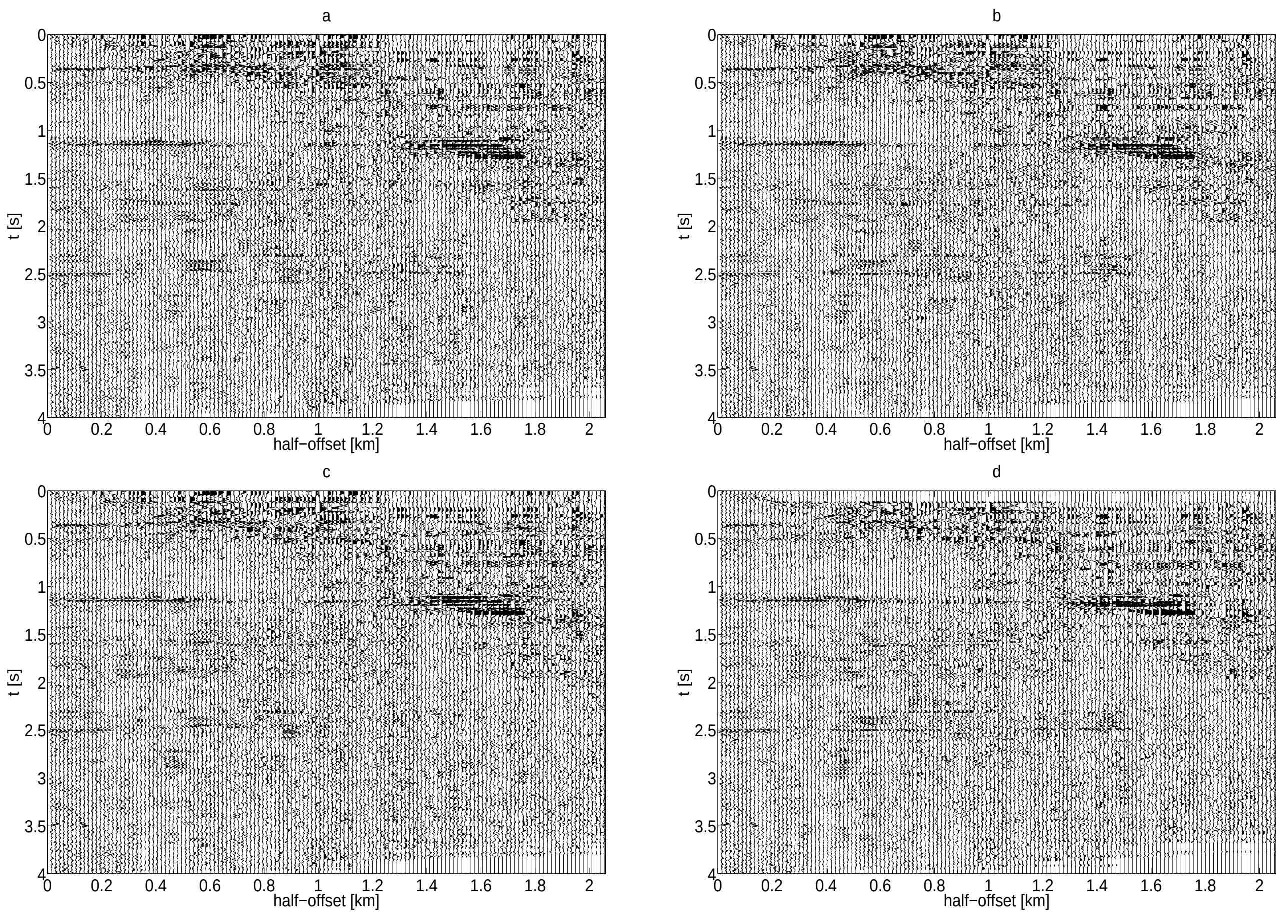

Figure 7: NMO correction applied to CMP section for velocities obtained by (a) conventional semblance, (b) minimum semblance, (c) weighted semblance and (d) AB semblance.