MULTICOMPONENT VELOCITY ANALYSIS BY MEANS OF COVARIANCE MEASURES AND COMPLEX MATCHED FILTERS

Velocity analysis for multicomponent data is revised in order to improve the accuracy of the velocity estimate and to combine information from horizontal and vertical components into a single panel.

Multicomponent OBC data are strongly contaminated by coherent noise such as torsional modes, mud rolls, multiples and ghosts. The reflections cannot be properly resolved by the standard semblance operator that is insensitive to coherent noises and is unable to distinguish between interfering events. Velocity estimation is improved by the use of a coherence measurement based on the decomposition into eigenstructures of the spatial covariance matrix as well as by the approximate a-priori knowledge of the wavelet amplitude spectrum.

The multicomponent panel, in which the velocity analysis is performed, is obtained by adding in quadrature the horizontal and the vertical responses. One of the main advantages is that the velocity analysis carried out on a single gather allows to speed up the velocity picking that, otherwise, has to be repeated for orthogonal panels. Moreover, lithologic bounds on the $V_p/V_s$ ratio can be checked because the trends of pure and converted waves are mapped together.

Tests performed on synthetic and real data show that the multicomponent velocity analysis provides accurate velocity estimations even for data at the early steps of processing.

The velocity analysis is carried out by measuring the coherence on trace samples selected along the hyperbolic trajectories that approximate the moveout curve. There are many methods for computing coherences: the most commonly used coherency measure is the semblance operator described as the normalised energy ratio between the output and input traces, where the output trace is obtained by stacking the input traces (Neidell and Taner, 1971).

Key and Smithson (1990) propose a coherence measure based on the eigenstructure of the data covariance matrix. Their implementation provides a high resolution of velocity spectra and is able to resolve reflections closely spaced in time and velocity.

Spagnolini et al. (1993) suggest to exploit the a-priori knowledge of the wavelet amplitude spectrum for the coherency measure and then propose the complex matched filter analysis. Even when the wavelet is approximate, the results indicate that the complex matched functional reject incoherent and coherent noise on synthetics as well as on real data (Grion et al., 1998). In this work we take advantages of both these methods by evaluating the eigensolutions of the covariance matrix of the data convolved with a complex matched filter.

We compute the coherence measure on a multicomponent panel in which the horizontal and vertical components are added in quadrature. For 3D acquisition the horizontal component can be obtained by means of the Karhunen-Loeve transform. With this approach, an approximate $V_p/V_s$ ratio can be computed from CMP gathers and the procedure iterated through horizontal CCP and vertical CMP gathers.
Following Key and Smithson (1990) we group the data collected within hyperbolic trajectories in super-traces allowing to reduce computational cost, to enhance the S/N ratio and to partially cancel interfering events. Afterwards, we apply a complex matched filter based on the a-priori knowledge of the wavelet (Spagnolini et al., 1993) and then we compute the covariance matrix.

Let $\lambda_i$ be the eigenvalues of the super-traces covariance matrix. Assume that noise and signals are uncorrelated with zero mean and variances $\sigma_N^2$ and $\sigma_S^2$, and the noise is uncorrelated from trace to trace and sample to sample. In the presence of signal along the trajectory,

$$\lambda_i = \sigma_S^2 + \sigma_N^2 \quad \text{and} \quad \lambda_i = \sigma_N^2 \quad \text{for} \quad 2 \leq i \leq M$$

(1)

where $M$ is the number of the super-traces.

The noise variance is estimated by averaging the lower eigenvalues as

$$\sigma_N^2 = \sum_{i=M}^{2} \frac{\lambda_i}{(M-1)}.$$  

(2)

According to equation (1), $\sigma_S^2$ is then computed.

To increase the sensitivity of the detection, Key and Smithson (1990) suggest to use a weighting function and propose a logarithmic one. Although the resolution is enhanced, several smears remain for trajectories that intersect reflections at far offsets; we use therefore the semblance operator as weighting function.

To obtain the multicomponent panel it is sufficient to add in quadrature the vertical and the horizontal components. In this way we obtain a panel constituted by analytical signals in which the coherence measures can be computed through the method described above.

The performance of the Covariance Measure with Complex Matched analysis (2CM) has been compared with other coherence measures such as the Semblance, the covariance measure (K&S) and the Complex Matched Analysis (CMA) on synthetic and on real data.

The example shown here comes from a real 2D data set pertaining to an OBC MC acquisition. The CMP gathers refer to a flat zone. After first breaks muting and band-pass filtering, a FK filter has been applied to remove the mud rolls. Torsional modes, which have moveout similar to the converted reflections, have not been removed from the data. Then, the resulting CMPs are still strongly contaminated by coherent noise (Fig. 1).

The Semblance analysis (Fig. 2a) is able to depict the general trends of velocities but significant ambiguities in the picking of velocity-time pairs exist. The K&S analysis weighted by the Semblance (Fig. 2b) provides better localized picks in the velocity direction but not in the time direction. Due to the high selectivity of the covariance methods and to the high signal to noise ratio of the data, the colour saturation inside the red boxes has been lowered to preserve visual resolution. By introducing the CMA (Fig. 2c) distinct picks are provided for many of the events before blurred, conversely low resolution is obtained in velocity. With 2CM analysis (Fig 2d) properly resolved events are obtained and events undistinguished with other coherence measures are highlighted.

MC velocity analysis on a single panel allows to perform a simultaneous interpretation of P and S velocity and thus to speed up the velocity picking. Also, a
priori information such as velocity logs, Vp/Vs trends and lithological bounds can be easily included as an aid to the interpreter.

**Fig. 1** - CMPs used for the computation of the coherence measures. On the left the horizontal component and on the right the vertical component.

Coherence measures based both on the covariance of the data along hyperbolic trajectories and on the complex matched analysis allow to resolve near and interfering events.

**Fig. 2** - Coherence measures obtained from Semblance, Key and Smithson, Complex Matched Analysis, Covariance Measure and Complex Matched filter. Both pure and converted velocity trends are evident on the panels. The red boxes in the panels obtained by the covariance matrix decomposition refer to zones with high signal-noise ratio that have been saturated with lower values.
Acknowledgements. We would like to thank David Ambrosin and Luciano Fontana for their help in the implementation of the code. The real data CMPs have been kindly provided by ENI E&P.

REFERENCES