



Structure-oriented filtering effect on seismic attributes

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Resumo

Structure-oriented filtering is an adaptation of coherency-enhancing anisotropic diffusion filters. It consists of a simulated anisotropic diffusion process (low-pass filter) that diffuses the seismic amplitude parallel to the reflections. It is based on the following equation:

$$\frac{\partial u}{\partial \tau} = \nabla (\mathbf{D} \nabla u), \quad (1)$$

where $u = u(x, y, t)$ is the seismic data, τ is the diffusion time and \mathbf{D} is the diffusion tensor, given by

$$\mathbf{D} = \sum_{i=2}^d \mathbf{v}_i \mathbf{v}_i^T. \quad (2)$$

In this construction, the direction associated with the largest eigenvector (the most significant data variance) is removed, so the diffusion flow must occur only in the other directions.

The structure-oriented filtering is a known method to remove noise and simplify structural information in seismic data. These qualities make it a valuable tool for improving automatized classification using machine learning techniques. Such techniques, in general, use seismic attributes that may be extracted from data before or after applying the filter. Applying the filter before attribute extraction can save computational time, but verifying the impact in classification is crucial.

In this work, we study the effects of structure-oriented filtering on attributes. We use a selection of seismic attributes used in classification, such as amplitude and its derivatives, instantaneous phase and its derivatives, thinbed, and bandwidth. We also employ Grey Level Co-occurrence Matrix (GLCM) attributes, such as inertia, prominence, and entropy. We employ some unsupervised methods for the classification of the data, including crossplotting, k-means, self-organized maps (SOM), and generative topographic mappings (GTM). Even though structure-oriented filtering introduces some changes to the attributes, they can still be used in the classification methods.