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VSP wavefield separation using structure tensor dip masking filter

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ABSTRACT In a Vertical Seismic Profiling (VSP) acquisition, downgoing wavefields and upgoing wavefields, interfere. Both wavefields are practical in various seismic applications, However, it is needed to separate these two reflection and transmission fields. Different techniques have been proposed for VSP wavefield separation. Median filtering as well as 2D Fourier transforms are commonly used for separating the seismic wavefields. The former suffers from the averaging effect, generating artifacts, and amplitude modification due to spectral energy leakage after the inverse transform. 2D Fourier has the problem of leakage and edge effects. We propose a new approach based on the structure tensor and local dip estimation following a masking filter for VSP wavefield separation. The dip masking filter is calculated using the local dip of each point of data that can separate upgoing and downgoing wavefields from the original data. The advantage of this approach is both in preserving seismic amplitudes and in provision of a section free of fake events; this literally implies no energy leakage. The synthetic and real data examples are demonstrated to show the performance of the proposed method.

Key words: VSP, wave separation, local dip, structure tensor, dip masking filter.

1. Introduction

Vertical Seismic Profiling (VSP) is a seismic technique that extracts high-resolution information from the subsurface. The seismic VSP signal is generated at the surface recorded by receivers located at different depths in a vertical well. VSP recorded data have been used in calculating the velocity and the attenuation in an interval (Pevzner *et al*., 2011; Baharvand Ahmadi and Morozov, 2013; Wang, 2014).

In a VSP recording, downgoing wavefields with a positive-slowness and upgoing wavefields with a negative-slowness, interfere with each other (Seeman and Horowicz, 1983; Hardage, 2000). The simultaneous recording of upgoing and downgoing wavefields are regarded as an added value of the VSP method. Downgoing waves are used to compute seismic P- and S-waves velocities, to calculate the seismic anelastic quality factor Q, to create time-dependent filters, which are used to recover high-frequency seismic waves (Sudhakar and Blias, 2002). Upgoing wavefields are tools for obtaining VSP-CDP images (Blias, 2005).

As a fundamental step to process a VSP data set, the separation of upgoing and downgoing wavefields is introduced. There are many methods to separate upgoing and downgoing signals from each other. Mostly these methods are based on two types: 1) methods using averaging filters for the separation of the upgoing and downgoing waves by median filter; 2) wave separation techniques which transform primary data into a new domain and separate upgoing and downgoing waves in this space and thereafter returning data to its primary space. The most important ones are f-k and τ-p filtering. Curvelets are also a kind of directional-scale tools used for VSP wavefield separation (Heravi *et al.*, 2012).

The median filter method (as a conventional wave separation technique) is based on flattening data for separating downgoing, then applying a classic median filter, shifting back and finally subtracting the separated downgoing wavefield from the original data to obtain the upgoing wavefields. In the median filter method, each sample is replaced by the median value of its neighbourhood samples. Therefore, due to the averaging effect, this method suffers from smoothing the input signal, manipulating primary signal amplitudes, and damaging some of the useful details. To cope with these problems, some improved versions of median filters or non-linear median filters have been proposed such as vector median filtering (Kasparis and Eichmann, 1987; Astola *et al.*, 1990) which has been applied in seismic data processing (Liu, 2013). Moreover, Chen *et al.* (2016) improved the signal preserving ability of a median filter using a structure-oriented space-varying median filter.

Wave separation techniques such as f-k or the τ-p, transform data in the new domain and always generating some artifacts events in this space is unavoidable and hence amplitude modification due to spectral energy leakage effect happens. In experimental physics, data spectral leakage is a well-known problem in the data domain transforms. Xu *et al.* (2005) proposed an antileakage Fourier transform approach for seismic data regularisation case. Chen *et al.* (2014) proposed an iterative framework for deblending of simultaneous-source seismic data using Seislet domain shaping regularisation and compared this method with two Fourier based transform; f-k domain thresholding, and f-x predictive filtering. According to their results, Fourier based transform methods suffer from energy leakage and generate artifacts.

Downgoing waves are characterised by positive apparent velocity and a negative slope in VSP image data, upgoing waves are characterised by negative apparent velocity and positive slope. In this paper, it is decided to use the dip variance and, then, the output is used to separate upgoing and downgoing wavefields from each other. So, data will not be transferred to the new space and as a result, data domain transfer does not yield the leakage of energy. In this paper, we decide to make a masking filter based on the local dip of each point of data which can separate upgoing and downgoing wavefields from original data. We called this method “dip masking filter” and the advantage is that neither averaging of amplitudes nor artificial event by transfer data happen; this implies no energy leakage.

An initial published work estimating dip directly from 2D seismic data is by Picou and Utzmann (1962). Finn and Backus (1986) extended dip estimation to 3D data as a piecewise continuous function of spatial position and seismic traveltime. Marfurt *et al.* (1998) generalise a later semblance-based scan by Finn and Backus (1986). As discussed by Marfurt (2006), the local reflection orientation can be described by reflection normal vector. Fomel (2002) used plane-wave destruction filter to compute reflection slopes. van Vliet and Verbeek (1995) present an estimate based on the gradient structure tensor. Chen and Ma (2014) proposed a dip-separated filtering using an adaptive empirical mode decomposition based on dip filter to separate the seismic data into a number of dip bands. This method says that the dip estimation is better when it is applied to dip-separated profiles.

Our proposed local dip masking filter, based on the structure tensor method, is used for the purpose of calculating dip variance. The coherent structure of seismic images yields to suppose good candidates for structure tensor application (van Vliet and Verbeek, 1995; Weickert, 1999; Fehmers and Höcker, 2003), which are a common tool to estimate the local orientation of image features. Tensor structure in seismics is used in estimating the orientations of the seismic structural characteristics such as reflection slope, stratigraphic features orientations, horizon interpretation, subsurface modelling, etc. (e.g. Li and Oldenburg, 2000; Bakker, 2002; Fehmers and Höcker, 2003; Marfurt, 2006; Hale, 2009; Wu and Hale, 2015a; Wu, 2017a, 2017b). Bakker (2002) and Wu and Hale (2015b) use structure tensors (e.g. van Vliet and Verbeek, 1995; Weickert, 1997) to estimate reflection orientations. Wu and Janson (2017) propose a directional structure tensor to estimate the orientations of reflections with steep and rapidly varying slopes.

Faraklioti and Petrou (2005) benefit from the use of structure tensors to analyse the seismic data. In this paper, the structure tensor algorithm is used to separate VSP wavefields images after finding their local dips.

2. Methodology

2.1. Estimating local dips using structure tensors

The structure tensor is the outer product of the image gradient with itself, which is also called gradient-square tensors. Structure tensor was developed primarily for edge detection (Förstner and Gülch, 1987), but it has been used for a wide range of problems in image processing.

Considering an image I($x.y$) the structure tensor S is defined as:

$$\mathrm{S} = \begin{pmatrix} \mathrm{K} * \mathrm{I}_x^2 & \mathrm{K} * \left(\mathrm{I}_X\, \mathrm{I}_y\right) \\ \mathrm{K} * \left(\mathrm{I}_X\, \mathrm{I}_y\right) & \mathrm{K} * \mathrm{I}_y^2 \end{pmatrix}, \tag{1}$$

where K is a smoothing kernel (e.g a Gaussian kernel), $*$ stands for convolution operator, I_x and I_y are the vertical and horizontal components of the gradient of the image I, respectively. In 2D, the structure tensor S is finally of n×m×2×2 where n×m is the size of the initial image I. Effectively, tensor structure obtains a 2×2 matrix at each pixel of the original image. By the eigendecomposition of the matrix S, we can obtain the orientation information in each pixel. In accordance with the principles of matrix eigenvector decomposition, the eigendecomposition of a 2D structure tensor is as follows:

$$\mathrm{S} = \begin{pmatrix} \mathrm{K} * \mathrm{I}_x^2 & \mathrm{K} * \left(\mathrm{I}_X\, \mathrm{I}_y\right) \\ \mathrm{K} * \left(\mathrm{I}_X\, \mathrm{I}_y\right) & \mathrm{K} * \mathrm{I}_y^2 \end{pmatrix} = \begin{pmatrix} u & v \end{pmatrix} \cdot \begin{pmatrix} \lambda_u & 0 \\ 0 & \lambda_v \end{pmatrix} \cdot \begin{pmatrix} u^T \\ v^T \end{pmatrix}, \tag{2}$$

$$\mathrm{S} = \lambda_u\, uu^T + \lambda_v\, vv^T. \tag{3}$$

where u and v are normalised eigenvectors corresponding to the eigenvalues λ_u, λ_v, respectively.

These eigenvectors provide an approximation of orientations of features in the 2D image (Fehmers and Höcker, 2003). This information can be visualised as an ellipse with two diameters which are equal to the eigenvalues and directed along their corresponding eigenvectors as shown in Fig. 1.

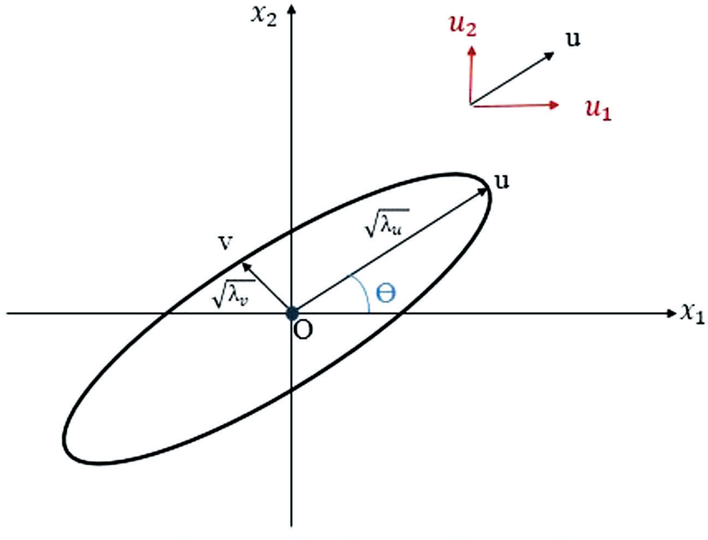

Fig. 1 - The structure tensor at point O is visualised as an ellipse and its unit eigenvectors u, v and rooted eigenvalues λ_u, λ_v are also depicted.

As shown in Fig. 1, the orthogonal eigenvectors u and v describe the orientation of feature in each point. Individually, for each sample, the eigenvector u, corresponding to the largest eigenvalue (λ_u), is parallel to the directions in which the image features vary most significantly. As shown in Fig. 1, the components of the unit vector $\hat{u}$ are related to local dips θ in each sample by:

$$u_1 = |u| \cos \theta, \tag{4}$$

$$u_2 = |u| \sin \theta, \tag{5}$$

Finally, the dominant orientation (local dip) in each sample is computed from the eigenvector u associated with λ_u as:

$$\text{dip } (0) = \tan^{-1}(^{u_2}/_{u_1}). \tag{6}$$

2.2. Wave separation process using dip masking filter

Using dip masking filter for VSP wavefield separation based on the structure tensor, the following steps are proposed:

1. application of a smoothing filter (e.g. with Gaussian kernel) on data to reduce random noise and non-structural orientations;
2. calculate the partial derivatives of the image and build structure tensor;
3. eigenvalue decomposition of the structure tensor;
4. estimate local dip over each sample;
5. use a moving similarity filter on dip image to obtain the dominant slope of each sample;
6. apply a median dip filter on data to eliminate noise points with non-structural directions;

7. create two dip masking filters by separate positive and negative obtained dips;
8. apply created dip masking filters on VSP data to separate upgoing and downgoing wavefields;
9. using the f-k interpolation to recovering intersecting points after apply masking filter.

In a noise-free data, the estimated orientation by structure tensor will be an ideal approximation for the slope of the events reported in sample by sample manner. But, in general, the presence of noise in the data will affect the estimated directions. In practice, mixing the content of coherent signal and random noise in seismic data is unavoidable. Therefore, we require to compute more stable dominant orientations by implementing a smoothing filter to each element of the gradient-based structure tensors. The smoothing helps to remove the noise and much more stable orientations even if apparently, the resolution of the input image is not good. In the algorithm presented, the first step, related to smoothing data before calculating the dip, is done with serious considerations. We proposed a recursive Gaussian filter for smoothing the parameters of window widths both in time and spatial directions, these must be optimally chosen for each input. It smoothes a few pixels whose values differ significantly from their neighborhood without affecting the other pixels. Note also that by increasing the size of the smoothing window, the structure tensor is robust in the presence of noisy data with less effect in reducing the spatial resolution [for more details about Gaussian filter and choosing optimum smoothing parameter refer to Deriche (1992), van Vliet *et al*. (1998) and Hale (2006, 2009)].

Steps 2, 3, and 4 are relevant in calculating local dip over each sample using structure tensors mentioned in section 2.1. Before creating masking filters from the estimated local dips, in addition to the smoothing in step 1, the algorithm performs the two additional steps 5 and 6 to deal with noise and estimated random orientations.

Step 5 is somewhat similar to the nonlocal algorithm for the image denoising, except that it does not refer to the image and is only applied to estimated directions from structure tensors. After computation of local directions in each sample, a matrix with 2×1 element is constructed at each pixel of the original image. Next, this matrix is decomposed into a number of vertical-horizontal overlapping small windows. For the central pixel of each window, the cosine similarity between this pixel and neighbourhoods is calculated and on the basis of the reported value, it is decided to keep/remove the direction for that pixel. A threshold similarity value by the user must be set in the algorithm. The schematic performance of this step is shown in Fig. 2.

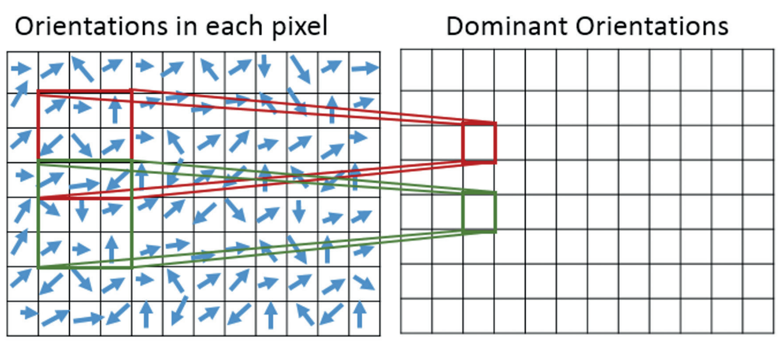

Fig. 2 - Schematic performance of moving similarity filter presented in step 5 on the dip image to obtain the dominant slope of each sample.

In step 6, a median filter is applied on data using the estimated dominant dip information, to eliminate noise points which have non-structural directions. In step 7, two dip masking filters are created by separate positive and negative calculated dips and the masking filters are applied accordingly on VSP data to separate upgoing and downgoing wavefields in step 8. Finally, in the last step, the f-k interpolation is used to recover intersecting points after application of the masking filter.

In general, our proposed method is not a noise removal method and, if there is significant noise in data, it is better to use denoising processes before.

3. Examples

3.1. Application on a synthetic model

To display the efficiency of the proposed method, it is firstly tested on a synthetic VSP data set. Fig. 3a shows a simple synthetic VSP data set containing a single downgoing and a single upgoing wavefield. Fig. 3b shows eigenvectors computed from structure tensors in each sample

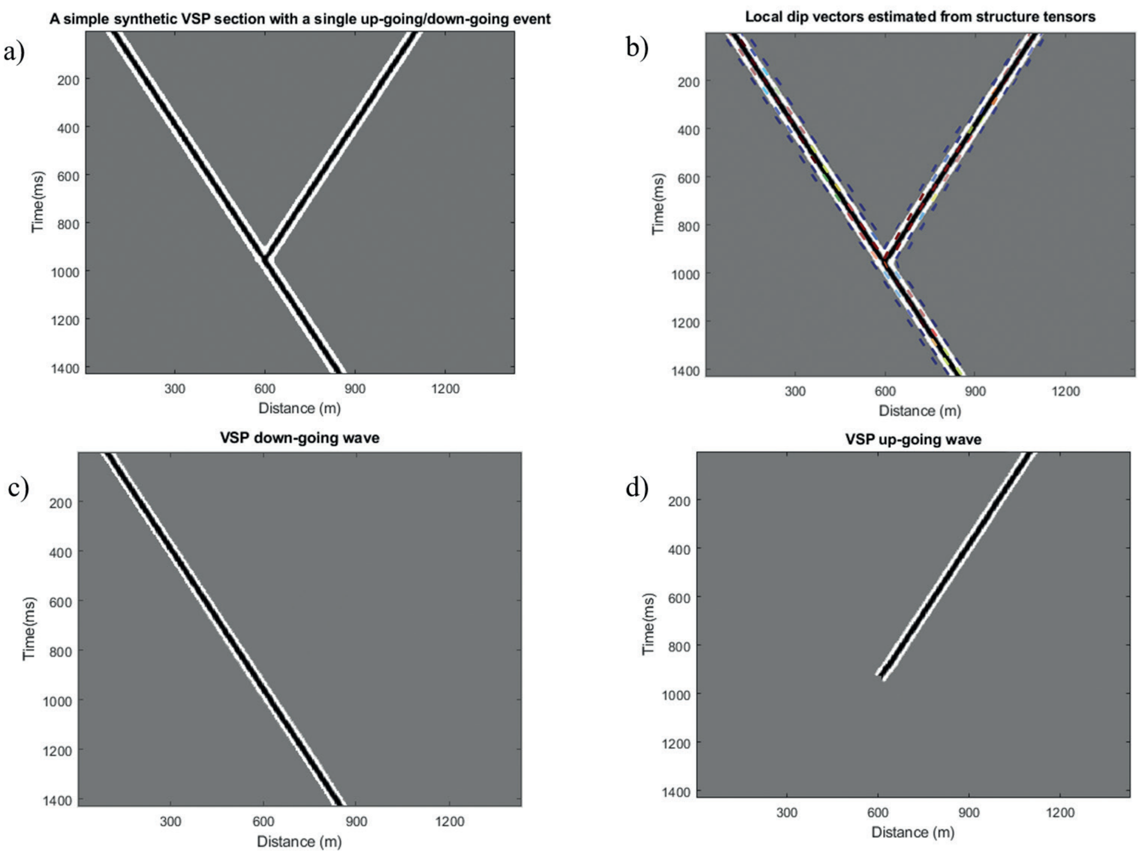

Fig. 3 - a) A simple synthetic VSP data set with a single upgoing and a single downgoing wavefield; b) eigenvectors computed from structure tensors in each sample exhibiting local structural orientation; c) and d) VSP downgoing and upgoing waves obtained from applying dip masking filter on synthetic data.

where structural orientations in these points are shown (for a better visualisation, 1 out of 20 eigenvectors in all images is shown).

After the creation of two dip masking filters, namely with positive and negative obtained dips, and performing the dip masking filter on synthetic VSP data, the separated downgoing and upgoing wavefields are obtained (Figs. 3c and 3d, respectively). As it is shown in Figs. 3c and 3d, the proposed method separates downgoing and upgoing wavefields from each other without artifacts or smoothing.

As shown in Fig. 3b, in this image all the orientations are correctly estimated by structural tensor and they contain three dominant directions: 1) a downgoing event with negative dip, 2) upgoing event with positive dip, and 3) background.

Now we add the Gaussian white noise to the primary synthetic VSP data set and compute eigenvectors calculated from structure tensors with and without the use of a smoothing filter. The results for the two noise values are shown in Figs. 4 and 5.

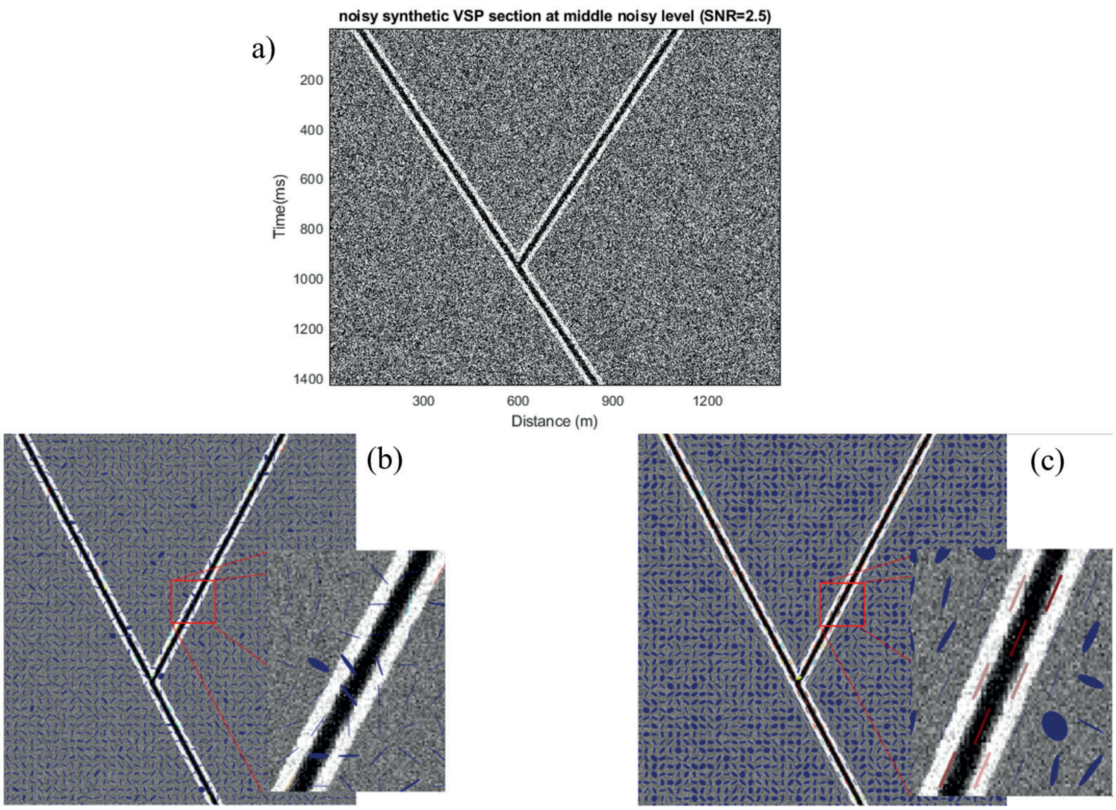

Fig. 4 - a) Noisy synthetic VSP data set corrupted by a middle level of Gaussian white noise; b) eigenvectors computed from structure tensors without the use of a smoothing filter; c) eigenvectors computed from structure tensors with the use of a Gaussian smoothing filter.

As shown in Figs. 4 and 5, the noise affects the estimated directions and causes the deviation of the slope approximation of the events. But, by using the smoothing filter on both images, the estimated orientations for dominant directions (upgoing and downgoing) are correctly calculated.

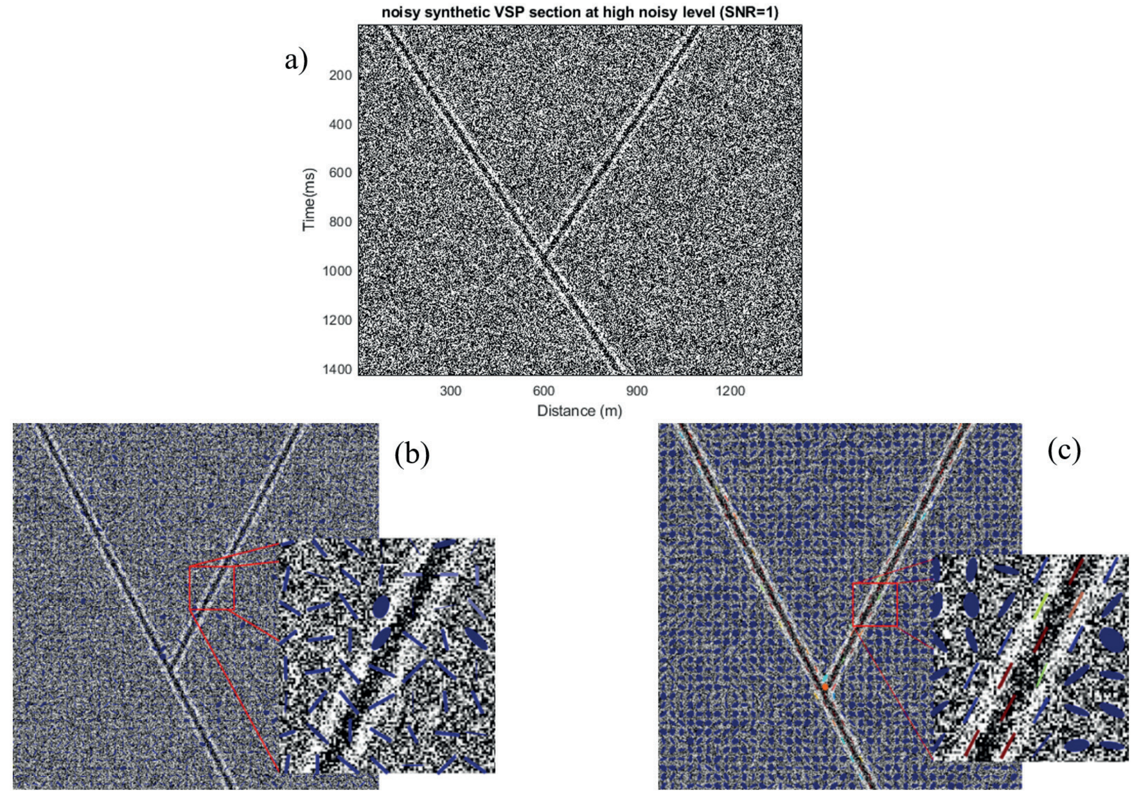

Fig. 5 - a) Noisy synthetic VSP data set corrupted by a high level of Gaussian white noise; b) eigenvectors computed from structure tensors without the use of a smoothing filter; c) eigenvectors computed from structure tensors with the use of a Gaussian smoothing filter.

3.2. The issue of intersecting waves

Structural tensors are a good estimator for finding the direction of the wave paths, but only for cases in which they do not intersect. Hence, the standard structural tensor breaks down in the presence of intersecting wavefields. In order to solve the difficulty in estimating correct conflicting dips, Chen (2016) proposed a dip-separated filtering approach. However, in this study our objective is to separate upgoing and downgoing wavefields in the simplest way with the lowest cost; it implies that the precise local slope estimation at the intersection point is not targeted.

For the case of two intersecting local orientations with different directions, the proposed approach can smartly represent only one of the dominant paths for the corresponding direction using f-k interpolation.

In Fig. 6a, a simple example of two waves with different local orientations is shown. Figs. 6b and 6c show the computed local dip vectors from structure tensors in each sample. As shown in this figure, at the intersection point only the most dominant direction is restored. After calculating the local dip at each point, the upgoing and downgoing masking filters are created by collecting positive and negative dips, respectively. Finally, the dip masking filters are applied on the input data (Fig. 6a) and the separated upgoing and downgoing wavefields are generated (Figs. 6d and 6e, respectively). As shown in Fig. 6c, only the upward direction is obtained at the intersection point, so in finding the masking filter, this area is assigned only to upgoing wavefield. Therefore,

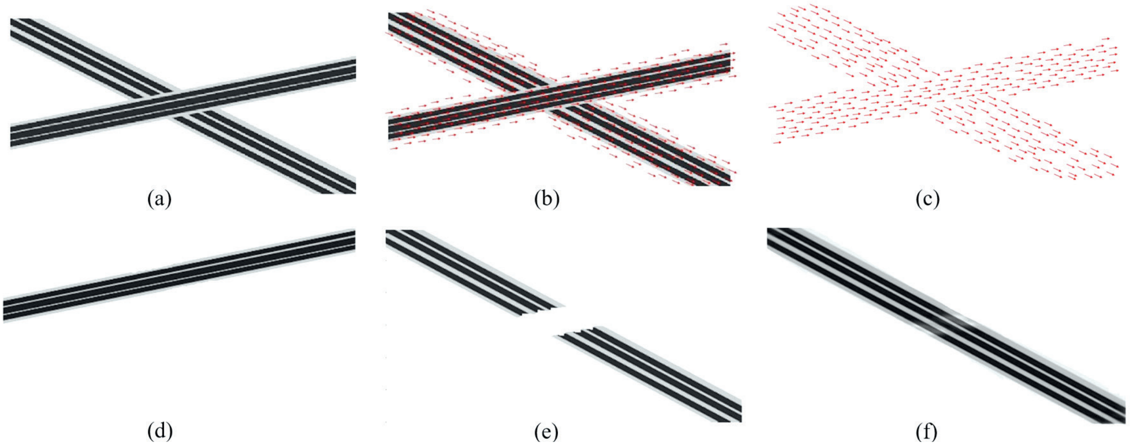

Fig. 6 - a) A a simple example of two waves with different local orientations; b) eigenvectors computed from structure tensors in each sample; c) eigenvectors in each point; d) upgoing events obtained from the application of the dip masking filter on primary data shown in panel a; e) downgoing events obtained from the application of the dip masking filter on primary data shown in panel a, at the intersection point, a discontinuity is observed in downgoing wavefield; f) downgoing wavefield after recovering by the f-k interpolation at the intersection point.

the nearby samples are incorrectly removed in downgoing wavefields and a discontinuity is observed in downgoing wavefield at this intersecting point (Fig. 6e).

In this paper, we use the f-k interpolation technique to recover intersecting points after applying a masking filter on data. Fig. 6f shows the downgoing wave after recovering by the f-k interpolation at the intersection point.

3.3. Real data example

We consider now a real vertical seismic profile from a 3D elastic simulation. This data set has been acquired in SEAM Phase I RPSEA based on the geology of the Gulf of Mexico. The described method gives us a tool to separate downgoing and upgoing wavefields. Fig. 7 shows this VSP data set consisting of downgoing and upgoing wavefields.

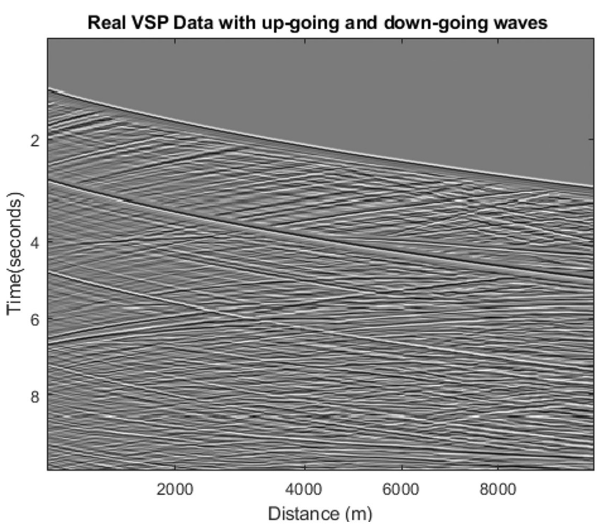

Fig. 7 - A real vertical seismic profile data set consisting of downgoing and upgoing wavefields.

Fig. 8 shows eigenvectors computed from structure tensors in each sample where there is a structural orientation in these points. These dominant directions help us to separate downgoing and upgoing events from each other.

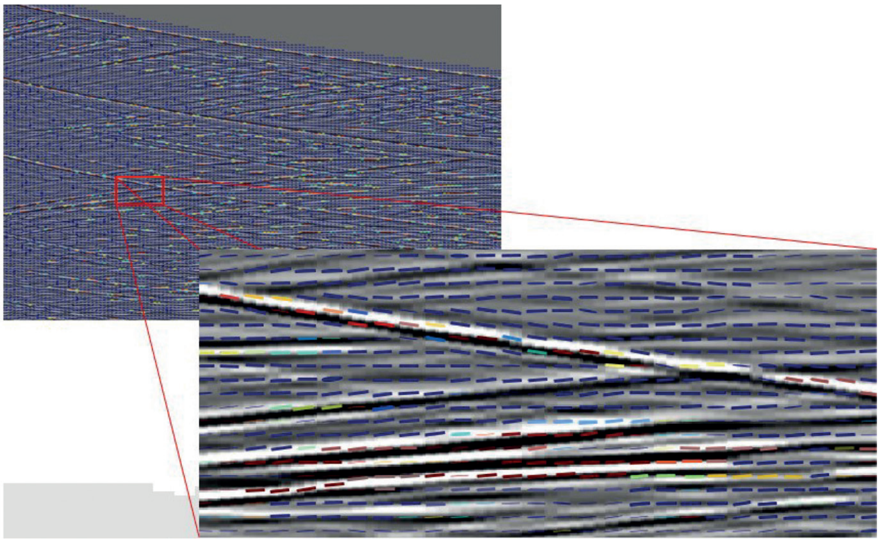

Fig. 8 - Eigenvectors computed from structure tensors in each sample. The direction of these eigenvectors can represent a local structural orientation in each sample (of course, for the presentation, the eigenvector of all the points is not drawn but only one out ten points).

After applying generated dip masking filters on the real VSP data shown in Fig. 7, the separated downgoing and upgoing wavefields are generated (Figs. 9a and 9b, respectively).

Fig. 9 shows the progression obtained by the dip masking filter in the upgoing and downgoing

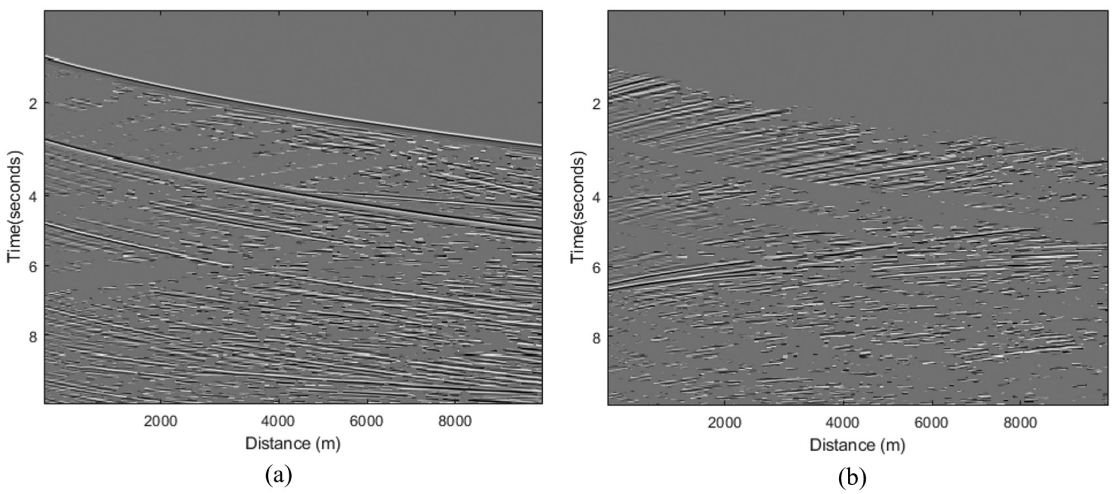

Fig. 9 - Downgoing events obtained from applying the dip masking filter on primary VSP data (a) and upgoing events (b).

separation. As it is clear in this figure, in points of discontinuity intersection in the upgoing and downgoing events continuity of events is lost. The solution presented here is the use of f-k interpolation in intersecting points.

Figs. 10a and 10b are the separated downgoing and upgoing wavefields after interpolation at the intersecting points. These figures highlight that the continuity of seismic events has been sufficiently recovered. The result of another standard wavefield separation method (flattening and subsequent median filtering) is shown in Figs. 11a and 11b.

Comparing the separation results obtained by the application of the median filter method (Fig. 11) with the proposed method (Fig. 10), it is clear that there is not significant interference of

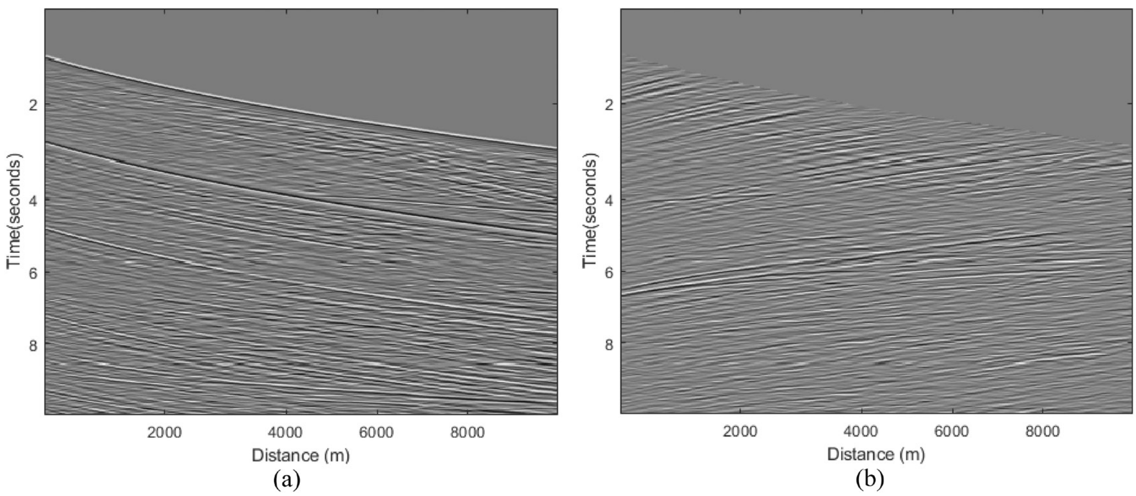

Fig. 10 - Downgoing separated wavefields recovered in intersection points by f-k interpolation (a) and upgoing wavefields after recovered (b).

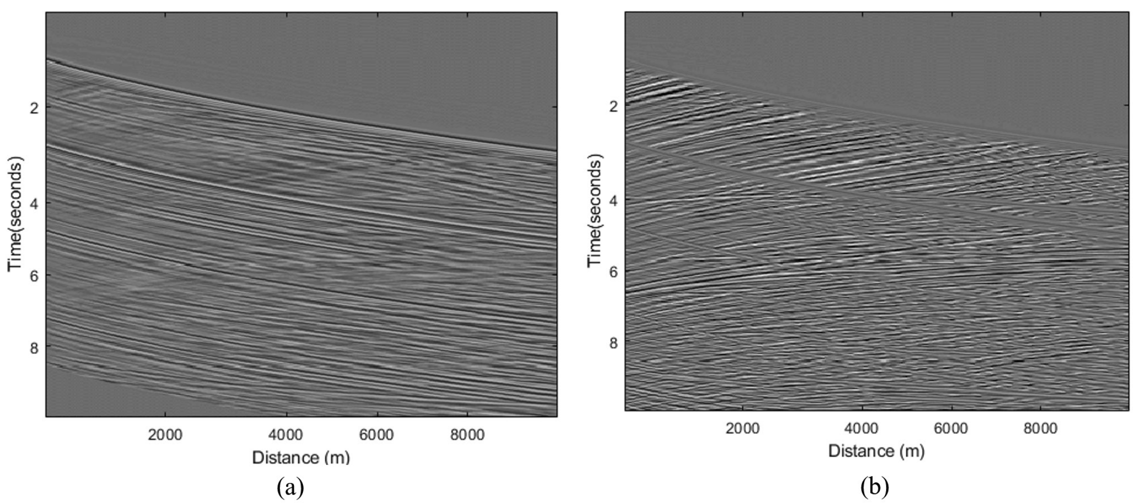

Fig. 11 - Downgoing separated (a) and upgoing wavefields obtained by median filter method (b).

downgoing events in the separated upgoing waves (Fig. 10b), but clearly, downgoing waves are visible in separated upgoing wavefield obtained by the median filter method (Fig. 11b).

Comparing the separation downgoing results, it appears the highly coherent visible output of standard median filtering algorithm. However, a further look to the computed histograms of amplitudes (Fig. 12) confirms that the median filtering has considerably changed the norm of amplitude values and distribution considerably. The similarity of Figs. 12a and 12b highly emphasises the amplitude preserving manner of the proposed method.

Furthermore, first break picking is a fundamental step in VSP wavefield separation by median filter method, any errors of these arrival times may have significant effects on the results. Another advantage of the proposed method is that it does not require these times.

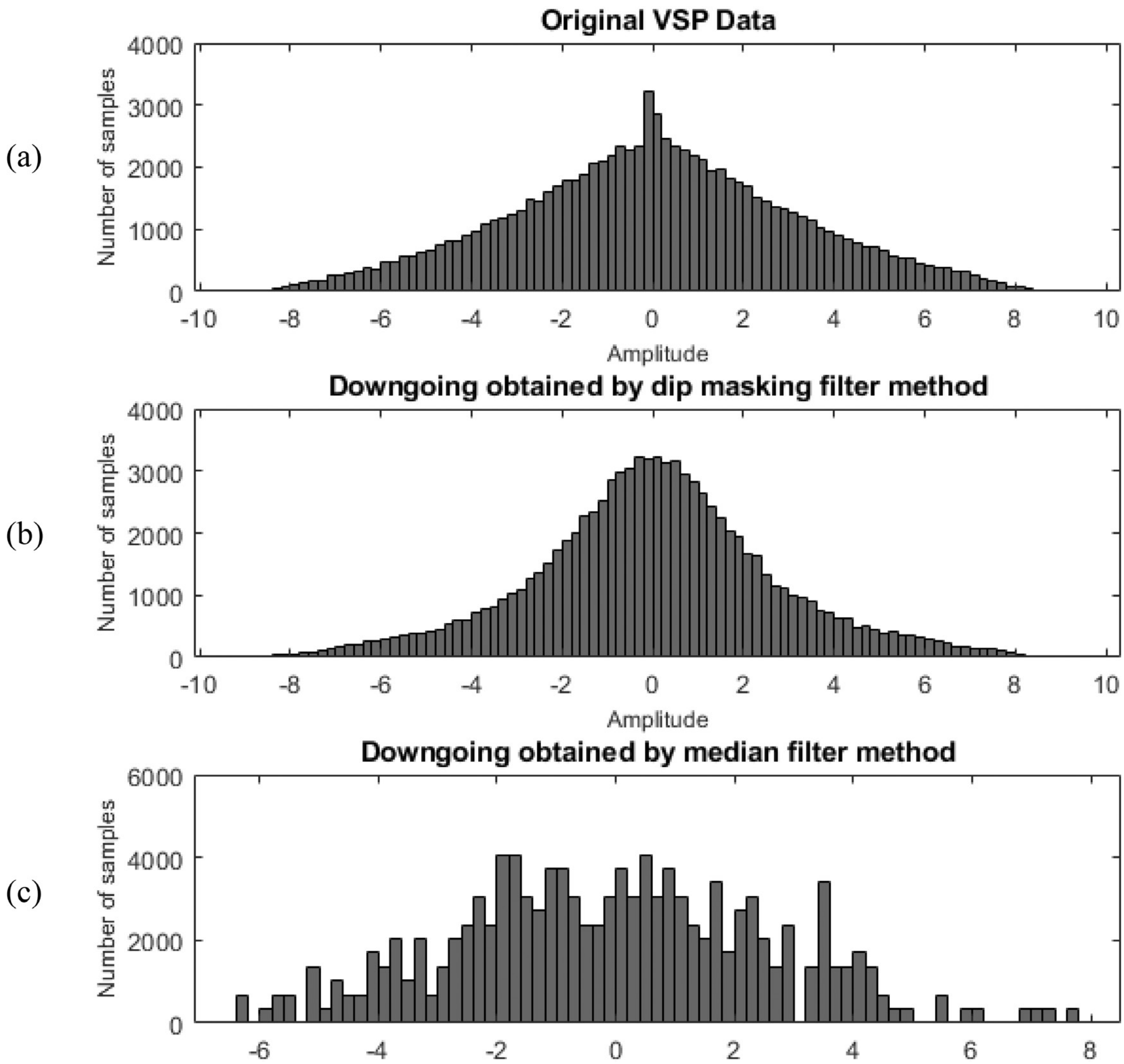

Fig. 12 - Histogram of amplitude of: a) original VSP data; b) downgoing wavefields obtained by dip masking filter, and c) downgoing wavefields obtained by median filter method.

4. Conclusion

In this paper, we have proposed a new approach, structure tensor followed by dip masking filter, to separate VSP downgoing and upgoing waves. The main idea of this method is the application of slope of events to separate upward and downward waves: we first generate a mask with the same size of data using the slopes derived from structure tensor, then, by applying the mask filter on data, we separate the upward and downward waves. This leads to no energy leakage (amplitude preserving manner) and the total energy after separation is equal to the initial input ensemble energy, despite that, in traditional methods, wave separation often occurs when data is transferred to a new space (f-k domain or τ-p domain).

Finally, it was shown that the approach presented in this paper performs well in separating VSP downgoing and upgoing waves and offers the advantage over conventional techniques that no averaging of amplitude of data occurs, so no artificial smoothing of the event is done and hence the leakage of energy is nearly zero.

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