Using principal component analysis to decouple seismic diffractions from specular reflections

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Summary

Methods developed for diffraction imaging are commonly based on a separation technique between continuous and discontinuous structural elements, based on their seismic response. Seismic imaging in the dip-angle domain decomposes direction-dependent images where the response of different structural elements is clearly distinguished. The subsurface structural geometry dictates a local dip-angle seismic signature of preferable scattering directions, accordingly. Assuming these signatures are uncorrelated, we propose a practical workflow for dip-angle domain principal component analysis as a comprehensive structural feature separator. Once the dip-angle images are transformed into their principal components, a back projection yields structural-specific images of the subsurface main building blocks. Our proposal emphasizes the strength of principal component analysis as a producer of probable geologic features from pre-stack dip-angle data. These should be incorporated as structural attributes to enhance seismic interpretation, reduce uncertainty and enable automation.

Introduction

Methods for diffraction imaging provide high-resolution images of small-scale discontinuities and isolated objects within the subsurface structure (Khaidukov et al., 2004). A common key ingredient for diffraction imaging is a technique that separates the seismic response of specular reflections from seismic diffractions, based on their characteristic kinematic and/or dynamic properties (Shtivelman and Keydar, 2004; Fomel et al., 2007; Moser and Howard, 2008). In particular, diffraction imaging via a reflection/diffraction separation in the dip-angle domain is one of the most intuitive approaches in use today. The imaged reflectors are indicated by a well-defined specular dip and show a stationary dip-angle response, as opposed to diffractors that are non-stationary in dip (Landa et al., 2008; Koren and Ravve, 2010; Dafni and Symes, 2017). Based on that distinction, dip-angle filters split the image into specular and non-specular parts. In the absence of the dominant reflectors, the latter part gives rise to an enhanced image of the diffractors.

Images of seismic diffractions frequently supplement structural interpretation workflows by highlighting the discontinuities of the overburden structure and associated geology. It is usually considered as an additional valuable seismic attribute, added to the interpretation process to reduce uncertainty and increase decision making fidelity. It is a common practice to incorporate the diffraction image attribute via principal component analysis (PCA). PCA is a statistical method based on an orthogonal transformation that converts a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components (PCs). In seismic interpretation, PCA is generally employed to cross-correlate between various accessible seismic attributes (such as the diffraction image) and spot the combination of those having interpretative significance (Roden et al., 2015). It is used, therefore, to reduce a large set of seismic attributes to indicate variations in the data, which often relate to plausible geologic features of interest.

PCA holds similar value for extracting meaningful signatures from pre-stack seismic data. By considering the pre-stack data as a set of individual observations, PCA combines the most correlative segments into a set of uncorrelated PCs. Accordingly, each PC projects a distinguished characteristic feature. Such an approach is of high interest for dip-angle domain imaging systems. As mentioned, seismic reflections and diffractions are distinguished by their signature in the dip-angle image domain, and are most likely to be separated by the PCA orthogonal transformation into distinct PCs. Serfaty et al. (2017) recently introduced a novel deep learning technique for automatic classification of structural elements like reflection surfaces, various types of diffractions, and noise. At the basis of this method, PCA is employed in the dip-angle image domain as a data pre-conditioner. The work by Serfaty et al. (2017) shows a remarkable fine-scale level of structural specification, highly attractive for automatic interpretation. Consequently, the current work emphasizes the strength of PCA as a feature separator, and positions it as a superior method for conditioning the dip-angle images for automatic classification. We demonstrate that PCA, by nature, is a powerful technique for decoupling the strong reflections from other non-specular features when the inputs are partial stacks of dip-angle image gathers. Hence, even in the absence of an overwhelming deep learning neural network, a satisfying level of structural separation is achieved. The results show a detailed image of seismic diffractors next to an image of specular reflectors.

Theory and Method

Our method is based on a 3D depth imaging system which decomposes the seismic data into full-azimuth dip-angle image gathers (Koren and Ravve, 2011). This dip-angle decomposition unfolds the migrated data of each imaging point, in situ, by its direction. The illustration in Figure 1 further explains the image decomposition by the dip-angle direction. It shows a coffee table object, and a set of cameras distributed 360 degrees around it. Each camera takes a direction-dependent snapshot of the table, and the sum of all snapshots aggregates the table's 3D picture. However, if the snapshots are examined individually, one can see that each is illuminating a different part of the table: The top camera sees the table's top surface only, the side cameras reveal the surfaces of the table's legs, and the corner cameras capture the table's tips and edges. Therefore, by collecting subsets of snapshots we can combine the characteristic building blocks of the object. Assuming that the table's surfaces and the table's tips and edges are uncorrelated features, PCA application is suitable to decouple between the two. Distinct PCs will project an image of the continuous surfaces and an image of the discontinuous tips and edges.

Similarly, each trace composing the dip-angle image gathers can be considered as an individual direction-dependent snapshot of the subsurface structure (see Figure 2). A 3D image is conventionally generated by stacking the gathers. However, some directions specifically illuminate specular reflection surfaces, while others illuminate the structure's discontinuities (i.e. diffraction elements). Assuming the dip-angle responses of different structural elements, such as reflectors and diffractors, are uncorrelated, a PCA application is expected to distinguish between these features by individual PCs, and resulting in a specular image and a diffraction image.

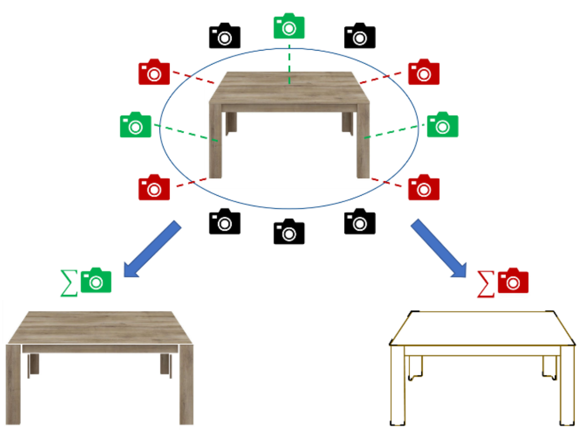

Figure 1: Distributing cameras around a coffee table object to compose its 3D image. A linear combination of direction-dependent snapshots produces a picture of the table's surfaces only (green snapshots) and a picture of the table's corners and edges only (red snapshots).

Examples

We demonstrate our method using field data acquired above the Eagle Ford shale play in south Texas. The Eagle Ford shale deposition occurred 90 million years ago at the top of the Woodbine group. It is the source rock for the overlying conventional Austin Chalk oil and gas reservoir.

A 3D depth image of the Eagle Ford data is computed by decomposing full-azimuth dip-angle image gathers (Koren and Ravve, 2011). Figure 2a shows an image section to the left of a single dip-angle image gather. The black mark indicates the gather location. The gather's traces are sampled simultaneously by both the dip angle and azimuth in a spiral order (Koren and Ravve, 2012). At the gather's location, a fault plane at depth 7000 ft, and a dipping reflector at depth 7800 ft are observed (red horizontal marks). These two structural elements exhibit two distinguished signatures in the dip-angle gather: A stationary response for the reflector and a non-stationary response for the fault. To better expose these characteristic signatures, we transform the gather's spiral sampling into a polar sampling. Figure 2b displays polar plots for the marked by red depths of the mentioned reflector and fault. The polar plots clearly indicate a stationary spot-like reflector, dipping north-west with ~20˚ dip-angle, and an azimuthally elongated pattern oriented north-west, as an indication of the fault plane azimuth.

In the following example we reorganize the dip-angle gathers into partial angle stacks prior to the PCA application. The gathers are split into 7 partial stack images by using a 10˚ dip-angle stacking interval, from 0˚ to 70˚. Hence, the PCA input consists of these 7 partial stacks in addition to the full angle stack, shown in Figure 2a. The PCA application first measures the spread (variance) and orientation (covariance) of the data by composing a covariance matrix for the input stacks, as introduced in Figure 3a. Our example shows two clusters of high variances, centered around the near-angle partial stacks and the far-angle partial stacks. The PCA then transforms the covariance matrix to its PCs, described by a set of Eigenvalues and Eigenvectors. Table 1 summarizes the Eigenvalues and their relative percent of contribution. The first 2 PCs are the most significant and compose almost one-half of the input data. Moreover, the Eigenvalue of the last PC is effectively zero and therefore ignored. Finally, the Eigenvectors back project the input stacks on the principal axes, so that correlated segments from the input data are collected into uncorrelated projections. A back-projection slice is displayed in Figure 3b. It expresses the correlation between the inputs (distinguished by color) and the first two PCs (the slice axes). One can roughly assume that the near-angle stacks and far-angle stacks highly correlate with the first and second PC, respectively. Figure 4 presents the back-projection results. The images are labeled by the PC number. A 3D view of the full stack is shown in the top-left corner for reference. By definition, the PCA back-projection produces a set of uncorrelated images. We consider the first PC projection as an image of the specular reflection elements, and the second PC projection as an image of the discontinuous elements associated with seismic diffractions. The fault network is well extracted by the latter along both the vertical and horizonal slices. The other projections expose some additional structural characteristics of the dip-angle dependent data. For example, the fourth and higher PC projections show an evident pattern of grid and acquisition footprint. Note that if the higher PCs hold a significant portion of the input data (as may be revealed in Table 1), it would be wise to obtain the reflection and diffraction images as a weighted linear combination of multiple PCs. For example, a linear combination of the second and third PC projections may generate a superior diffraction image, exposing a more structurally plausible result. We co-render these two images in Figure 4, middle row, rightmost panel, by using a different color code.

Conclusions

Seismic imaging in the dip-angle domain produces images that are closely related to the subsurface structural geometry. Each dip-angle image is a direction-dependent snapshot of the earth's interior. We have demonstrated by principal component analysis a practical workflow for decomposing the dip-angle data into images associated with the principal structural elements. The most probable elements are continuous reflection surfaces and small-scale discontinuous features, associated with seismic diffractions. As a byproduct, segments of coherent noise are distinguished by the minor principal components, which leads to their rejection. The significance of the imaged features exposed by the principal components is implied directly by their Eigenvalues. Moreover, deeper investigation is accessible via analysis of the Eigenvectors projection slices and the covariance matrix shape. The images projected by the major principal components are valuable structural attributes for seismic interpretation. Moreover, they are extracted directly from pre-stack dip-angle data, and not from the mere image stack. As demonstrated by Serfaty et al. (2017), when a deep learning framework is introduced on top of the dip-angle domain principal component analysis, a high level of structural specification may be achieved as a substantial step towards automatic interpretation and structural classification.

Acknowledgements

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PC #	*Eigen Value*	*Contribution %*	*Cumulated Contribution %*
1	2.32577	29.0721	29.0721
2	1.53995	19.2494	48.3215
3	1.11420	13.9276	62.2491
4	1.00007	12.5009	74.7500
5	0.844432	10.5554	85.3054
6	0.642033	8.02541	93.3308
7	0.533518	6.66897	99.9998
8	1.73701e-05	0.000217126	100

Table 1: A trasformation of the dip-angle stacks into the principal system, described by Eigenvalues and their percent of contribution.

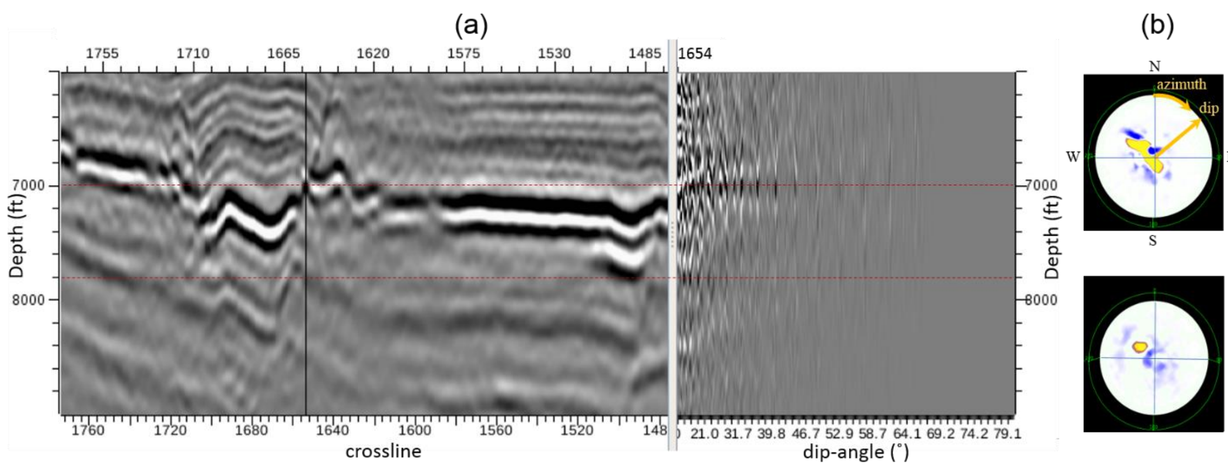

Figure 2: Eagle Ford shale data example. (a) An image stack to the left of a full-azimuth dip-angle image gather, extracted at the marked in black location. The red horizontal marks intersect a fault plane (depth 7000 ft) and a dipping-reflector (depth 7800 ft) at the gather's location. (b) At these depths, the dip-angle image gather is decomposed into polar plots showing the dip-angle signatures of the fault (top) and the reflector (bottom).

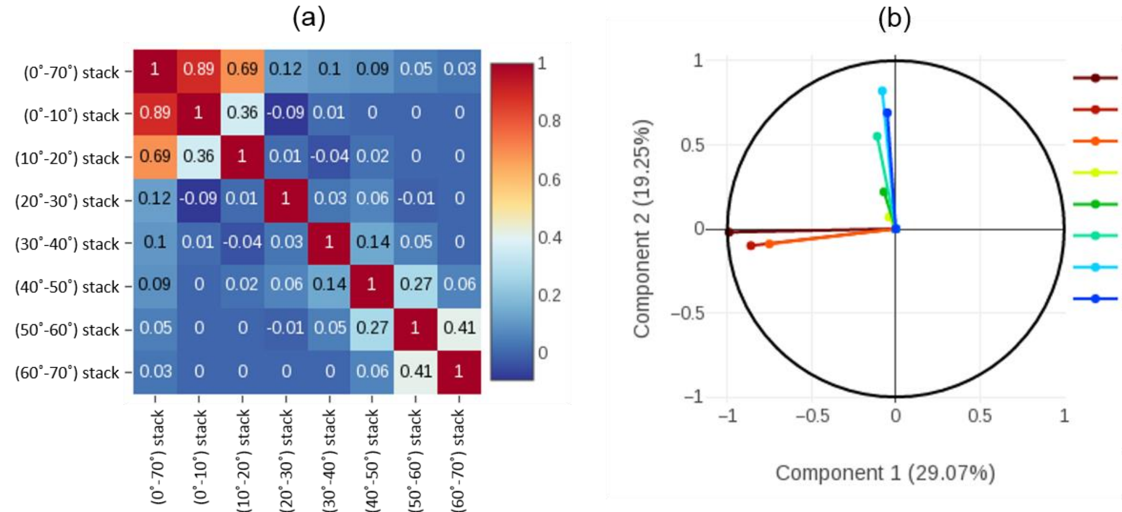

Figure 3: Eagle Ford shale data example. (a) The covariance matrix of the input dip-angle stacks. (b) Back-projecting the dip-angle stacks on the principal axes by the Eigenvectors. A projection slice is shown with respect to the first two PCs.

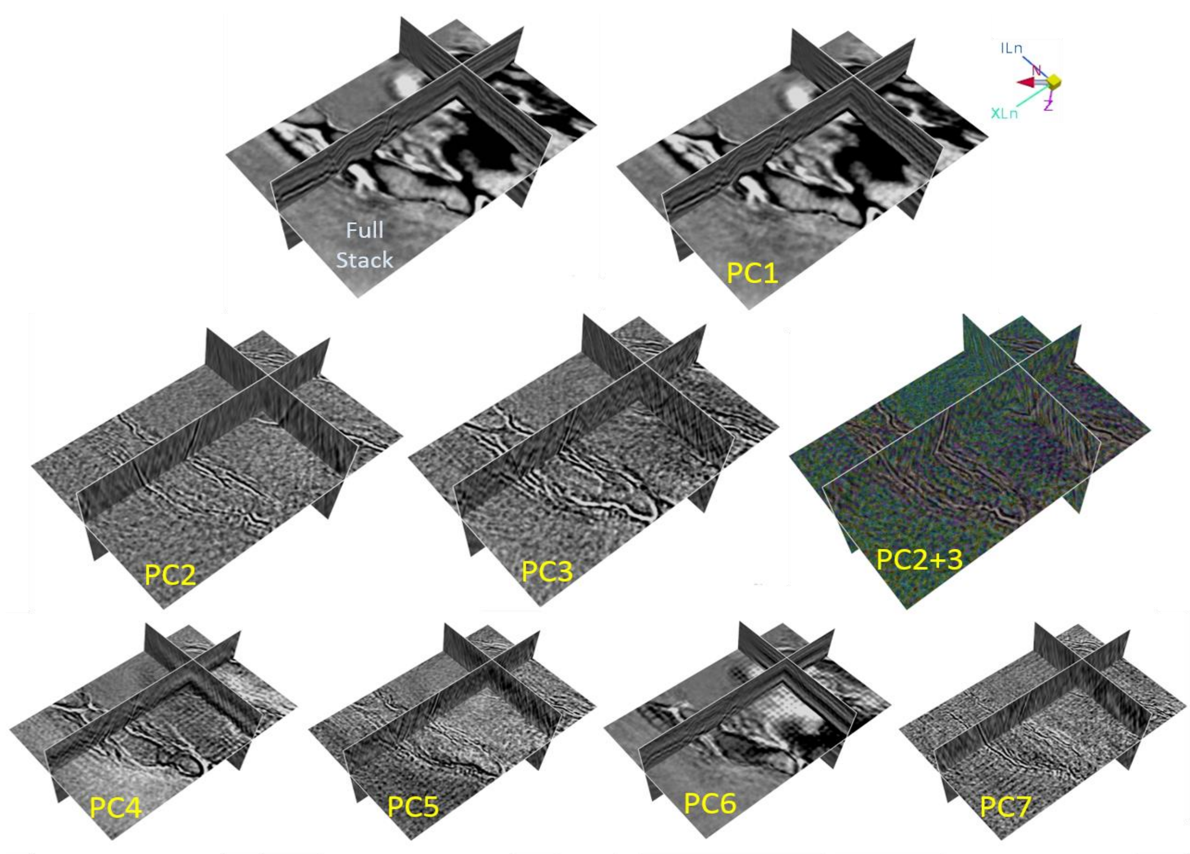

Figure 4: Back-projecting the dip-angle stacks on the principal axes by the Eigenvectors produces the PC images (numbered). The dip-angle full stack is shown for reference. Useful structural specifications may be obtained by co-rendering multiple PC images.