Utilizing Rotational Data for Seismic Polarization Analysis and Filtering of Vertical Component Data

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Summary

Field data recorded by a new rotational 6-degree-of-freedom sensor have been analysed. Rotational components were used for evaluating the polarization vector of the seismic events in the data and a polarization-based filter was designed to reject rotational data from vertical component data in chosen directions. The polarization approach shows positive results when applied to field data but also indicates the need for some improvements.

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Introduction

In geophysical studies, polarization estimated from three component seismic data is often used to analyse the directionality and origin of seismic waves such as P and S body waves and surface waves. In this study, we present a new approach for analysing the polarization characteristics of seismic waves recorded by a six-component (6-C) sensor, capable of measuring translational and rotational data.

In our approach we use three rotational records to estimate the polarization vectors of the 3D rotational wavefield. This allows us to remove signal waveforms of rotational origin from the vertical record.

The filtering method used in the process is adaptive, selectively eliminating only seismic events that originate from rotation and are aligned with the estimated polarization vectors. This filtering approach preserves the non-rotational energy in the data. The designed approach is not constrained to purely polarized waves or a pure state of seismic events, so we do not consider it to be a classification scheme of seismic events at this stage.

We provide seismic data examples from the North Sea and Gulf of Mexico. Our findings suggest that use of rotational records can lead to improved polarization analysis and separation of seismic events based on their directionality.

Method

In this study, we use 6-C data acquired using a new 6-degree-of-freedom (6-DOF) sensor, *Ksphere*, which measures translational accelerations along the three-coordinate axes and rotational accelerations about these axes (Pedersen et al., 2023).

We start by transforming the rotational accelerations to rotational velocities $r_x(t), r_y(t), r_z(t)$ to make them spectrally comparable to the translational measurements. Subsequently, we define a polarization vector by searching for an eigenvector of the covariance matrix, as described by Vidale (1986) and Greenhalgh et al. (1990) for 3-C data, Pinnegar (2006) and Sollberger et al. (2018) for 6-C data. In the presence of rotational signals in the vertical translational component, this polarization vector will point towards an axis of rotation where the contribution of rotational energy is occurring (in the plane perpendicular to that axis).

The covariance matrix is calculated in several steps, see Sollberger et al. (2023). We start with converting all measurements to analytic signals, denoted by capital letters. Recall that the analytic form of a signal $r(t)$ is defined as $R(t) \coloneqq r(t) + i\mathcal{H}(r(t))$, with $\mathcal{H}$ denoting the Hilbert transform. For the rotational data, we thus get:

$$[r_x, r_y, r_z] \mapsto \vec{R}(t) \coloneqq [R_x(t), R_y(t), R_z(t)]^T. \quad (1)$$

We subsequently apply the S-transform to the components of the rotational data vector to obtain their representations in the time-frequency domain $\tilde{R}_x(\tau, f), \tilde{R}_y(\tau, f), \tilde{R}_z(\tau, f)$. The symbol '~' denotes an S-transformed signal. Subsequently, we define the covariance matrix as:

$$C(\tau, f) = \vec{\tilde{R}}(\tau, f)\vec{\tilde{R}}^H(\tau, f). \quad (2)$$

Finally, we apply an averaging operator over a window of size $\Delta\tau$ in time and Δf in frequency to all elements of this covariance matrix and denote the result by $C_w(\tau, f)$.

We solve the eigenvalue problem for matrix $C_w(\tau, f)$, which is Hermitian and has three real non-negative eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$ and three corresponding complex eigenvectors $\vec{v}_1, \vec{v}_2, \vec{v}_3$ for each point (τ, f). In this paper, we use the eigenvector $\vec{v}_1$ associated with the largest eigenvalue, which has the direction of the rotational axis of the dominant rotational signal at the point (τ, f).

The eigenvector is normalized by maximizing the length of the real part of the eigenvector, as described in Vidale, 1986. This normalization approach defines the dominant rotational direction as the major axis of the polarization ellipse.

We project the rotational data vector $\vec{\vec{R}}(\tau, f)$ onto $\vec{v}_1$, apply the inverse S-transform, and subtract the result from the vertical acceleration record:

$$A_z(t)_{filtered} = A_z(t) - \alpha\, S^{-1}\left(\vec{v}_1^H(\tau, f)\vec{\vec{R}}(\tau, f)\right). \tag{3}$$

where the filter α is determined by minimizing the energy of the righthand side in a full nodal gather. The adaptive subtraction in formula (3) bears resemblance to the methods published by Pedersen et al. (2023), Masoomzadeh et al. (2024), and Seher et al. (2024).

Test Results

We tested the proposed approach on *Ksphere* data from the North Sea (shallow water) and Gulf of Mexico (deep water). Figures 1 and 3 show the vertical translational acceleration and 3 rotational records for a single far offset shot line from each location, respectively.

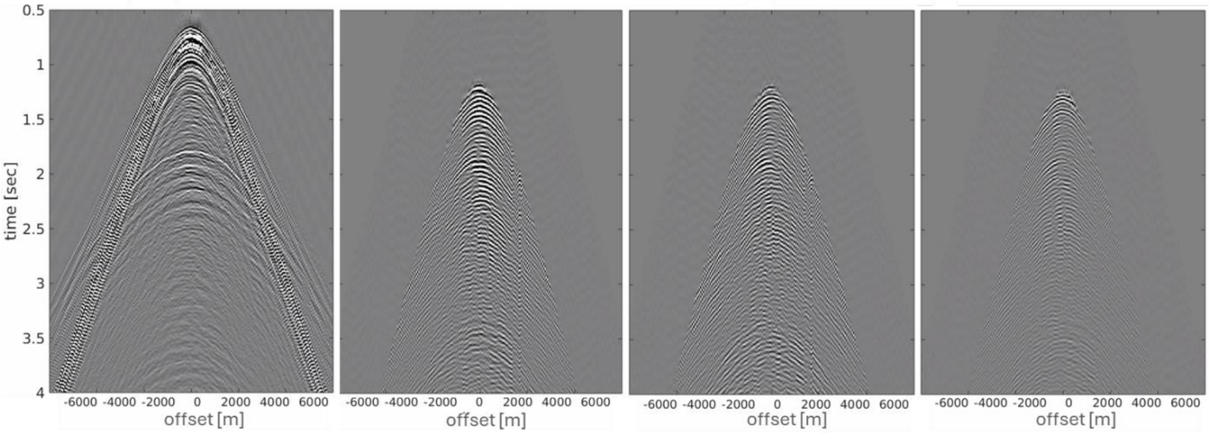

***Figure 1:** Ksphere nodal records from the North Sea: vertical acceleration (left). Rotational accelerations about x-, y- and z- axes (second, third and fourth pictures from the left).*

Results from the proposed filtering method for removing rotational energy from the vertical component are displayed in Figure 2 (North Sea) and Figure 4 (Gulf of Mexico). The left section shows the *Ksphere* vertical translational component, while the middle section displays the filtered vertical component. The right section presents the hydrophone gather for comparison.

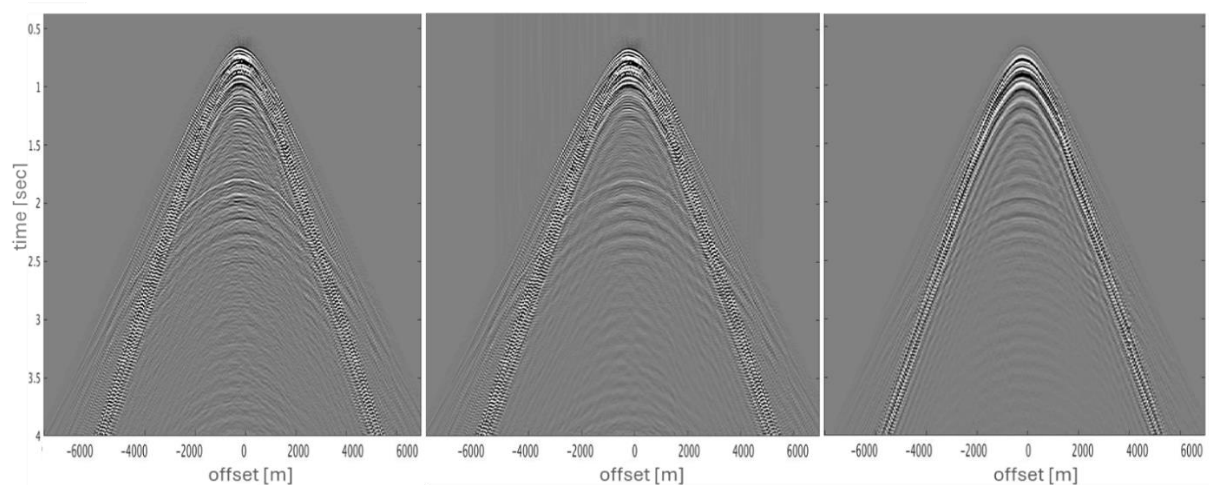

***Figure 2:** Ksphere data from the North Sea. Vertical acceleration input (left) and polarization filtered vertical acceleration data (centre) and hydrophone data (right).*

Figure 4 shows results from subtracting rotational wave energy from the vertical component in the Gulf of Mexico example.

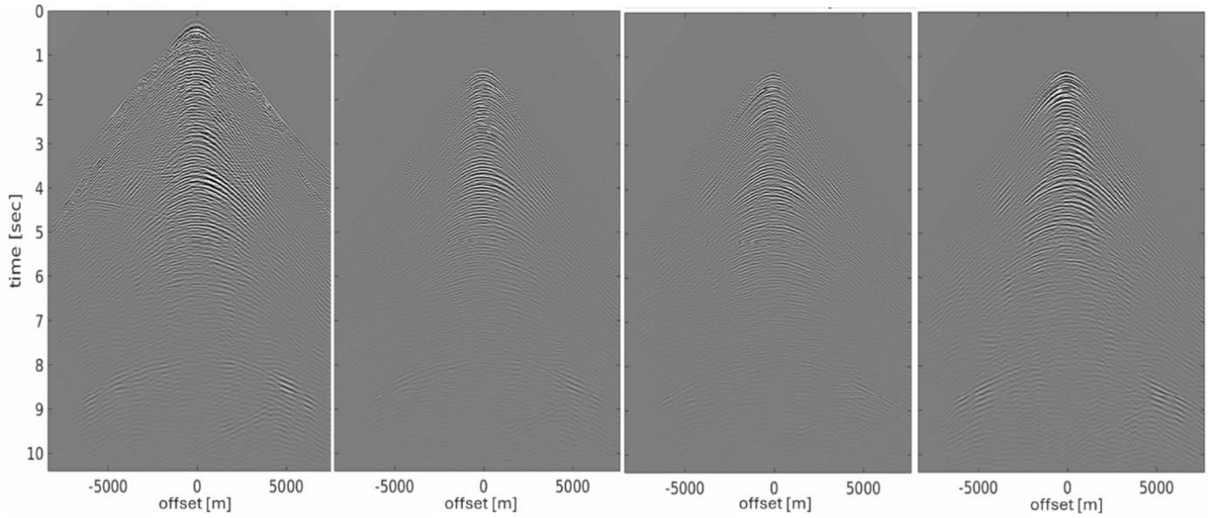

Figure 3: *Ksphere nodal records from the Gulf of Mexico: vertical acceleration (left), rotational accelerations about x-, y- and z-axes (second, third and fourth pictures from the left).*

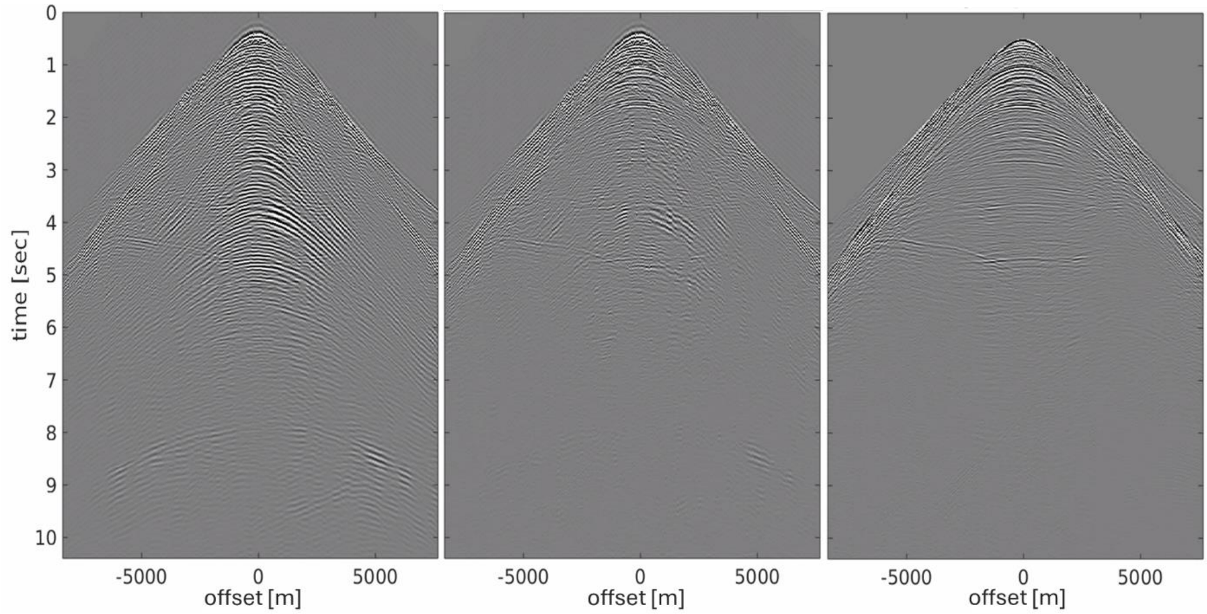

Figure 4: *Ksphere data from Gulf of Mexico: vertical acceleration before (left) and after polarization filtering (centre) and hydrophone gather (right).*

Discussion

The eigenvector directionality approach helps to effectively reduce rotational energy in the vertical record, allowing for the recovery of the compressional energy of non-rotational origin in the data. The polarization approach shows good results for the North Sea records. Specifically, the rotational energy is concentrated in a narrow-offset range around zero and mostly in the XY plane, with noticeably weaker amplitudes than the primary energy (particularly for rotations about the vertical axis). In our view, this makes the task of estimating the polarization vector and subtracting the rotational energy easier.

However, the analysis of Gulf of Mexico data revealed a significantly higher level of rotational energy, especially in the seismic traces related to rotation about the vertical axes, which may indicate complex subsurface geology or geometry: the medium near the sensor may not be homogeneous and isotropic, or the water bottom may not be flat. After subtracting the rotational energy, some residuals were observed (Figure 4). There are several possible explanations for this, including: (**i**) the eigensolution of the matrix with rotational records may not provide accurate estimates for polarization directions, which could be due to a suboptimal time window used in the analysis; (**ii**) the subsurface reflections in these offsets may be too complex for the polarization analysis to accurately resolve the 3D rotational wavefield acquired by a 6-C sensor from a single far offset shot line; (**iii**) the sensors may not be properly oriented. Further development of the proposed method may be necessary to better understand the potential of using the full eigenvector spectrum. These remnants can be attenuated by standard curvelet domain methods, provided there is a dip- and frequency discrimination between *compressional* and non- *compressional* energy.

Conclusions

Using real data from the new 6-DOF rotational *Ksphere* sensor, we applied polarization analysis to the rotational records to decompose the rotational data into a new orthogonal basis that corresponds to eigensolutions of the cross-correlation matrix of the 3 rotational records. The rotational wavefield is decomposed in the eigenvector's axes basis. The projections of the vertical component and rotational components in the eigenvector's basis align collinearly.

Application of the new method on two field data sets proves that rotational and translation data are related in the polarization analysis and share the same directionality pattern which can be matched in eigenvector space. By projecting rotational data onto the eigenvector basis and subtracting it from the vertical component data, we have observed that directionality is a crucial characteristic for analysing rotational wave fields. This approach has the potential to be used for wave field separation and event classification.

The polarization approach demonstrated convincing results for the shallow water example (Figure 2). However, subtraction of rotational energy shows significant residuals in the Gulf of Mexico example which can be attributed to either subsurface complexity or inaccurate wavefield representation. Further analysis and processing will be carried out to clarify these initial findings and improve the method.

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