An image-guided method for automatically picking common-image-point gathers

Thomas Cullison* and Paul Sava, Center for Wave Phenomena, Colorado School of Mines

SUMMARY

Using common-image-point gathers (CIPs) instead of conventional image gathers for migration velocity analysis is an efficient approach for analyzing migrated images at locations that are related to geological structures. This approach reduces computational costs and may improve migration velocity analysis by accounting for diving energy. However, manually picking CIP locations is tedious and time-consuming, especially for 3D images; therefore, an automated method for picking CIPs is desirable. To take advantage of the potential computational cost savings, CIPs should be constructed at relatively sparse locations throughout an image. Furthermore, to facilitate improved analysis, CIPs should be constructed along geological features. We provide a new method for automatically picking CIP locations from seismic images. This method uses local image properties including planarity, structure-oriented semblance, and the amplitude envelope to compute a priority-map (PMAP) of seismic images, where higher PMAP values indicate better CIP locations. After the priority map is computed, CIP locations are picked sparsely throughout the image using a greedy heuristic.

INTRODUCTION

Wavefield-based depth migration is commonly used for creating accurate seismic images of complex subsurface geology. However, the accuracy of migrated images is strongly related to the accuracy of the velocity models that were used for migration. Therefore, generating accurate velocity models for migration is necessary for accurate imaging (Gray et al., 2001).

Migration velocity analysis (MVA) is a strategy that uses wavefields for estimating and improving the accuracy of velocity models. In MVA, an objective function is formulated after migration and image attributes are analyzed for indications of velocity model inaccuracies (Sava and Vasconcelos, 2011). These attributes are typically represented by image extensions using image-gathers. These gathers can be analyzed for velocity error using the semblance principle which states that image-gathers are flat or focused when velocity models are correct (Shen et al., 2003; Stolk et al., 2005). Using this principle, velocity models can be built based on objective functions that optimize for image-gather features such as focusing or flattening (Al-Yahya, 1989; Symes, 2008).

Sava and Vasconcelos (2011) suggest that using common-image-point gathers (CIPs) instead of common-image-gathers (CIGs) for MVA has several advantages. First, CIPs are constructed for a single image point which allows the image to dictate the location and sparseness of CIPs. In contrast, for computational efficiency, CIGs are typically constructed at every depth location for fixed surface coordinates. Therefore, the image can be undersampled laterally and oversampled vertically. Second, CIPs can provide useful velocity analysis for reflectors with arbitrary dip. In contrast, CIGs provide useful velocity analysis only for nearly horizontal reflectors (Sava and Vasconcelos, 2011).

Manually picking CIP locations from complex seismic images is a time-consuming task, especially for 3D images. Therefore, if CIPs are used for MVA, it’s essential to use an automated method for picking CIP locations. Furthermore, because features and properties of the image should dictate the placement of CIPs, any automated method should use measurable image properties to guide the picking.

In this paper, we propose an automated method for picking CIP locations from seismic images that is based on measurable image properties. The method has two stages. In the first stage, a priority-map (PMAP) is created which assigns a value to each image location based on measurable image properties. In the second stage, a greedy heuristic is used to automatically pick CIP locations based on the PMAP values.

COMMON-IMAGE-POINT GATHERS

Common-image-point gathers (CIPs) are extended images constructed at fixed positions of space, and they can be used for MVA to analyze and correct for velocity model inaccuracies (Sava and Vasconcelos, 2011). However, accurate velocity analysis using CIPs may only be applicable when several assumptions are valid. It is assumed that source and receiver wavefields as well as the reflector can be approximated by planes within the vicinity of the CIP location. Furthermore, it is assumed that the velocity is locally constant in this vicinity as well. At the locations where these assumptions are invalid, CIPs may not be usable for MVA. This includes locations where the subsurface may have strong velocity discontinuities such as at the interface of a salt body, at diffractors, or along faults because of discontinuous geologic units. Therefore, CIPs should be constructed at locations that are along coherent reflectors that have simple structure.

Figure 1 shows an image of the Sigsbee-2A data which were migrated using the correct velocity. The CIP constructed at point A, shown in Figure 2(a), is located near the center of a coherent reflector that has simple structure. Notice that this CIP has strong focusing near the
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zero-crossing of the $\lambda_x$ and $\tau$ axes. This focusing property is useful for MVA (Sava and Vasconcelos, 2011). An example of a CIP constructed at a location where the planar assumption breaks down is shown in Figure 2(b). This CIP was constructed at point B in Figure 1 which is located at the edge of a salt body. Notice the lack of focusing near the zero-crossing of the $\lambda_x$ and $\tau$ axes.

When a CIP is constructed off the center of a reflector, focusing may also not occur near the zero-crossing of the $\lambda_x$ and $\tau$ axes even if the wavefields have been reconstructed using the correct velocity. Therefore, CIPs should be constructed near the center of reflectors.

The issue we have now is how to determine whether or not a location in a seismic image (a pixel or voxel) is near the center of a coherent reflector that has simple structure. This issue is addressed in our method by creating a priority-map (PMAP) which emphasizes locations that are near the center of coherent reflectors that have simple structure, and then using a greedy picking heuristic which picks CIP locations by favoring the locations that have greater emphasis in the PMAP (higher PMAP values).

**PRIORITY-MAP**

The PMAP is constructed by multiplying together measurable image properties including planarity, structure-oriented semblance, and the amplitude envelope. These image properties act as proxies for the desired qualities discussed above, and by multiplying these properties together, greater emphasis is placed on the locations that have the best combinations of these image properties. A manually defined mask can also be applied to the PMAP to exclude the construction of CIPs at locations that are within specific sections of an image such as within salt or water bodies.

To get a measurement of the planarity of an image, a structure tensor field for the image is computed. Structure tensors provide a means for obtaining local orientations of anisotropic image features (Vliet and Verbeek, 1995). A structure tensor is a smoothed outer product of image gradients, and it is often referred to as the gradient squared tensor (Fehmers and Hocker, 2003; Hale, 2009b). Similar to the gradient, structure tensors contain estimates of magnitude and direction; however, due to the smoothing, the magnitudes and directional vectors that are derived from a structure tensor are weighted averages.

To get a local measurement of planarity from the structure tensors, the eigen decomposition of each tensor is computed (Hale, 2009b). The eigen decomposition of a 3D structure tensor $T$ is

$$ T = \lambda_u u u^T + \lambda_v v v^T + \lambda_w w w^T, $$

where $u$, $v$, and $w$ are the eigenvectors that correspond to the non-negative eigenvalues $\lambda_u$, $\lambda_v$, and $\lambda_w$ of $T$. The eigenvalues of $T$ are sorted and labeled such that $\lambda_u \geq \lambda_v \geq \lambda_w \geq 0$. The eigenvectors $u$ are aligned in the direction where the image gradient is greatest, and the eigenvectors $w$ are aligned in the direction where the image gradient is weakest. Therefore, eigenvectors $u$ are orthogonal to local planar image features, eigenvectors $v$ are parallel to linear image features, and both eigenvectors $v$ and $w$ are parallel to planar features (Hale, 2009b).

The measure of planarity of local image features is derived from the eigenvalues $\lambda_u$ and $\lambda_v$. As described by Hale (2009b), the planarity measure $\lambda_p$ is defined as $\lambda_p = \frac{\lambda_u}{\lambda_v}$, where $0 \leq \lambda_p \leq 1$. The planarity measure is used to constrain CIP locations to regions in the image that have planar reflectors, and by clipping the planarity values that are below a user-defined threshold to zero, CIP locations are better constrained to these regions.

Structure-oriented semblance provides a normalized measure of the structurally dependent coherence of an image, and it can be used to constrain CIP locations to image features (reflectors) that are coherent and have simple structure. The method we use to compute structure-oriented semblance is described by Hale (2009b).

The structure-oriented semblance is used to constrain CIP locations to regions that have greater planar semblance values (i.e., coherent reflectors with simple structure). Similar to the clipping of the planarity values,
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Figure 3: (a) The image of the SEAM data and (b) the corresponding PMAP.

when the semblance values below a user-defined threshold are clipped to zero, CIP locations are better constrained.

To provide a measure of the distance to the center of a reflector, the vertical amplitude envelope of an image is computed, and then an automatic gain control is applied to the envelope to boost the amplitudes of weaker reflectors. If the weaker amplitudes are not boosted, CIP locations at strong reflectors are overly favored by the greedy picking heuristic which is discussed in the following section.

It is also possible to manually exclude the construction of CIPs from specific sections of an image (e.g., water or salt bodies) by creating a mask.

GREEDY PICKING HEURISTIC

A greedy heuristic is used to pick CIP locations based on the PMAP or both the PMAP and local image structure. The greedy heuristic maintains a sorted list of the PMAP values for each image location. This list is sorted in monotonically decreasing order. The procedure starts by picking the location that has the greatest PMAP value, and any location that is within a region (exclusion zone) that surrounds this pick is excluded from being picked in the future. Next, the heuristic picks – from the locations that have not already been picked or excluded – the location that has the greatest PMAP value. This process is repeated until each location has either been picked, excluded, or has a PMAP value that is equal to zero.

Exclusion zones are used to enforce sparseness between picked CIP locations, and these are either isotropic or anisotropic regions. Isotropic exclusion zones (IEZs) are spherical regions and their size is determined by a user-defined radius. Anisotropic exclusion zones (AEZs) are non-Euclidean ellipsoidal regions that semi-conform to the structure of local image features, and their size and shape are determined by a metric tensor field \( \mathbf{D}(x) \) and an eikonal equation. The metric tensor field is derived from a structure tensor field \( \mathbf{T}(x) \) of an image and a user-defined parameter which controls the non-Euclidean eccentricity of the AEZs. For each AEZ at a picked location \( x_0 \), an eikonal equation is solved for a measure of distance \( t(x) \) between \( x_0 \) and all points \( x \) that are within a distance \( t_{\text{max}} \) (in voxels) from \( x_0 \). The distances \( t(x) \) are numerically solved using a fast iterative method described by Jeong et al. (2007) and an eikonal equation described by Hale (2009a). This eikonal equation is defined as

\[
\nabla t(x) \cdot \mathbf{D}(x) \nabla t(x) = 1, \tag{2}
\]

where \( t(x_0) = 0 \) is the boundary condition and the distance \( t(x) \) is a non-Euclidean distance. The metric tensor \( \mathbf{D} \) is defined as

\[
\mathbf{D} = e_u \mathbf{uu}^T + \mathbf{vv}^T + \mathbf{ww}^T, \tag{3}
\]

where \( e_u \) is the non-Euclidean eccentricity parameter and \( 0 < e_u \leq 1 \). When \( e_u = 1 \), an AEZ is isotropic and
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equivalent to an IEZ.

Figure 5: CIP picks computed from the PMAP shown in Figure 3(a).

Each time the greedy heuristic picks a location $x_0$, the boundary condition of equation (2) is set to $t(x_0) = 0$, and all locations $x$ that have not already been picked or excluded and that are a distance $t(x) < t_{max}$ are excluded from being picked in the future. Figure 4 shows an example of an AEZ computed for the SEAM image. For this AEZ, $t_{max} = 20$ voxels and $e_u = 0.05$. If $t_{max}$ were decreased, then the size of the AEZ would decrease. If $e_u$ were decreased, then the thickness of the AEZ would decrease in the cross-structure direction, and vice-versa.

Figure 6: A bird’s-eye view of the tensor ellipsoids computed for each pick shown in Figure 5.

RESULTS

The picks shown in Figure 5 were selected from the PMAP using IEZs, and they are plotted with the PMAP instead of the image because it is easier to see the picks in 3D. The quality of picks can be visually verified by plotting the picks on the image and rotating, translating, and zooming in on the image as well as sliding the 2D panels back and forth and up and down. The majority of the picks shown in Figure 5 lie along the center of coherent reflectors that have simple structure, and the picks sample the image somewhat uniformly.

To assist with the verification of 3D picks, a user can also plot tensor ellipsoids at each picked location. The method used to compute these ellipsoids is described by Engelsma and Hale (2009). These ellipsoids conform to the local image structure both in shape and in orientation. Ideally, these ellipsoids should be disk shaped because the PMAP should constrain the picks to simple, coherent, planar reflectors. Figures 6 and 7 show the ellipsoids plotted for the picks shown in Figure 5. The overwhelming majority of the ellipsoids are disk shaped. Notice that the orientations (dips and strikes) of the ellipsoids correspond to the orientations of the local image features.

Figure 7: A side view of the tensor ellipsoids for each pick shown in Figure 5.

CONCLUSIONS

To be most effective for MVA, CIPs need to be constructed at sparse locations throughout an image, and they need to be constructed near the center of coherent reflectors that have simple structure. However, picking CIP locations by hand is a tedious and time-consuming process. The method described in this paper is both fast and effective at automatically picking sparse CIP locations that are guided by the image.

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