Applying the phase congruency algorithm to seismic data slices – A carbonate case study

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INTRODUCTION

Traditionally, the analysis of seismic data has involved looking for continuous events on seismic data, from which structural and stratigraphic features can be mapped. However, we are also interested in mapping discontinuous features such as faults and fractures. A method for identifying such discontinuities, the coherency algorithm, was first introduced by Bahorich and Farmer (1995), and is based on cross-correlating adjacent traces. Although the coherency method has undergone several major enhancements since its introduction (Gersztenkorn and Marfurt, 1999), it has remained the industry standard for identifying seismic discontinuities. However, researchers in other areas of image analysis, such as robot vision and feature identification, have also been looking at ways to identify discontinuities on their images. One such development is the phase congruency algorithm (Kovesi, 1996), which is able to identify corners and edges on images of shapes to enhance robot vision. We have recently implemented the phase congruency algorithm in a seismic analysis toolbox. In this article we apply this algorithm to seismic data slices to look for discontinuities. We will first discuss the theory of phase congruency and then apply the method to a simple robot vision example consisting of two overlapping shapes. We then apply the method to two seismic case studies, the first involving karst collapse features and the second involving a fractured carbonate reservoir.

THEORY OF PHASE CONGRUENCY

The phase congruency (PC) algorithm was developed to detect corners and edges on two-dimensional (2D) digital images (Kovesi, 1996). To understand the concept behind phase congruency in 2D space, it is instructive to first understand the algorithm in one dimension (1D). Figure 1(a), from Kovesi (2003), shows four terms in the Fourier series for a step function. Note that these terms are all in-phase at the
step, and therefore an analysis of their phase components would indicate the presence of the step. To quantify this concept, Kovesi (2003) plots the real and imaginary values for all four terms in the polar plot shown in Figure 1(b). We then line up the vectors as shown in the figure, with their related amplitude and phase values for all four terms. Extending this to $n$ terms, and using the notation used in Figure 1(b), Kovesi (2003) shows that phase congruency in 1D space is given by

$$PC(x) = \frac{|E(x)|}{\sum_n A_n(x)} = \frac{\sum_n A_n(x) \cos(\phi_n(x) - \bar{\phi}(x))}{\sum_n A_n(x)},$$ (1)

where $A_n(x)$ and $\phi_n(x)$ are the length and phase angle of each of the individual $n$ amplitude vectors, and $E(x)$ and $\bar{\phi}(x)$ are the length and phase angle of the summed vectors.

Kovesi (2003) then shows how to extend equation (1) to the two-dimensional image domain. This is done using oriented 2D Gabor wavelets in the Fourier domain. In the initial implementation, Kovesi used 2D Gaussian wavelets, but in a later implementation he used log Gabor wavelets, as introduced by Field (1987). The advantage of the log Gabor transform when used for the radial filtering is that it is Gaussian on a logarithmic scale and thus has better high-frequency characteristics than the traditional Gabor transform (Cook et al., 2006).

A flow chart for this method is shown in Figure 2. This basic algorithm is extended by using weighting and noise thresholding terms (for details, see Kovesi, 2003). As can be seen in Figure 2, the first step in the 2D phase congruency algorithm is to transform the data to the 2D Fourier domain. We then compute and apply $NM$ filters ($N$ radial log Gabor filters multiplied by $M$ angular filters). The log Gabor filters are computed over $N$ scales $S$, where $S = 0, \ldots, N-1$. Typically, the value of $N$ is between 4 and 8. Each log Gabor filter is computed by the formula

$$\log Gabor_S = \exp \left[ -\frac{\ln(r \cdot \lambda_S)^2}{\sigma} \right] \cdot lp,$$ (2)
where \( r \) = the radius from zero frequency, \( \lambda_s = 3m^8 \) is the scale value, with a default value of \( m = 2.1 \), \( \sigma = 2\ln(0.55) \) is the width of the log Gaussian function and \( lp \) is a low-pass 2D Butterworth filter. The angular filters are created over \( M \) orientation angles \( \theta \), where \( \theta = 0, \pi/M, \ldots, (M-1)\pi/M \). The default value of \( M \) is 6, in which case the angles will range from \( 0^o \) to \( 150^o \) in increments of \( 30^o \). After the \( NM \) filters are applied, each filtered image is transformed back to the spatial domain and, after appropriate weighting and noise thresholding, is summed over the scales to produce an image at each orientation. These images are then analyzed using moment analysis, which is equivalent to performing singular value decomposition on the phase congruency covariance matrix (Kovesi, 2003). The maximum moment \( M \) and minimum moment \( m \) are computed as follows:

\[
M = \frac{1}{2} \left( c + a + \sqrt{b^2 + (a - c)^2} \right),
\]

\[
m = \frac{1}{2} \left( c + a - \sqrt{b^2 + (a - c)^2} \right),
\]

where \( a = \sum_{\theta \neq d_0} (PC(\theta) \cos \theta)^2 \), \( b = 2 \sum_{\theta \neq d_0} \left[ (PC(\theta) \cos \theta)(PC(\theta) \sin \theta) \right] \), and \( c = \sum_{\theta \neq d_0} (PC(\theta) \sin \theta)^2 \).

The magnitude of the maximum moment indicates the significance of an edge feature on the image. The magnitude of the minimum moment gives an indication of a corner on the image. In this study, we will display only the maximum moment \( M \), since we are interested in edge features.

**A SIMPLE EXAMPLE**

Let us now look at applying phase congruency to a simple example. Since the original algorithm was developed to identify features on a 2D photograph, we used an image consisting of a cylinder of amplitude 2 superimposed on a cube of amplitude 1 and a background of amplitude 0, shown in perspective view in Figure 3(a) and map view in Figure 3(b). The amplitude-coded map in Figure 3(b) is presented to the phase congruency algorithm.
Figure 4(a) next shows the perspective view of the real component of the 2D Fourier transform of the image, and Figure 4(b) shows the same display in map view. After the 2D Fourier transform, the first step is the creation of the filters. We used four scales (with $m = 2.1$) and six orientations. Figure 5 shows the perspective plots of the four log Gabor filters, from $S = 0$ to $S = 3$. As expected, the filters get more "spiky" as the scale increases. The map views of the four filters are shown in Figure 6. Next, the map views of the six angular filters are shown in Figure 7. (The perspective views are not shown.) Finally, Figure 8 shows the 24 individual filters in groups of six corresponding to the angle range for each scale. Again, these are only shown in map view.

The filters shown in Figure 8 were then applied to the 2D Fourier transform of the image shown in Figure 4 and their inverse transforms are computed. We then stack these inverse transforms over the scales for each angle and apply moment analysis. The final result is shown in Figure 9(b), with the initial image shown in Figure 9(a) for reference. Notice how well the edges of the two structures have been defined. Of course, the example just shown is extremely simple and was used only to illustrate the algorithm. In the following sections, we will therefore apply the phase congruency algorithm to seismic data slices.

**IMPLEMENTATION ON 3D SEISMIC VOLUMES**

A schematic diagram showing the way in which the phase congruency method was implemented on seismic data is shown in Figure 10. Although this algorithm proceeds by analyzing constant time slices, it should also be possible to apply the algorithm to structural, or stratigraphic, slices. We will next implement the phase congruency algorithm on several seismic examples. The first example will be a karst collapse study from the Boonsville area of north Texas, and the second example will be from a fractured carbonate reservoir in Alberta.
KARST COLLAPSE CASE STUDY

We will first analyze a 3D dataset from Boonsville, Texas. The wells and 3D seismic from this dataset are in the public domain, and are available from the Bureau of Economic Geology at the University of Texas. The geology of the area and exploration objectives of the Boonsville dataset have been fully described by Hardage et al. (1996) and a map of the area taken from that paper is shown in Figure 11.

In the Boonsville gas field, production is from the Bend conglomerate, a middle Pennsylvanian clastic deposited in a fluvio-deltaic environment (Hardage et al., 1996). Figure 12 shows inline 141 from the 3D seismic volume over the gas field. An event close to the top of the Bend formation (the Davis) is shown at approximately 930 ms, and the base of the Bend formation is indicated by the third picked event at 1050 ms, the Vineyard. The Bend formation is underlain by Paleozoic carbonates, the deepest being the Ellenburger Group of Ordovician age. The Ellenburger contains numerous karst collapse features which extend up to 760 m from basement through the Bend conglomerate (Hardage et al., 1996). As can be seen in Figure 12, these karst collapse features, illustrated by the vertical ellipses, have a significant effect on the basal Vineyard event and continue vertically almost until the Davis event. Hardage et al. (1996) demonstrate, using measured pressure data, that these karst collapse features affect reservoir compartmentalization within the producing Bend formation. The karst collapse features are also evident when we look at the time structure map from the Davis horizon (the top picked event on the seismic section in Figure 12), as shown in Figure 13. The circular anomalies on this structure map clearly show these karst collapse features. Also shown is the position of inline 141 from Figure 12, which cuts two of the anomalies.

We will now try to identify these karst collapse features using both the phase congruency and coherency methods. Figure 14 shows a set of composite slices (in the X, Y and Z directions) over the 3D seismic survey illustrated by the white outline in Figures 13(a) and (b), where Figure 14(a) shows the original seismic survey and Figure 14(b) shows the phase congruency results. On Figure 14(a) the Y-direction, or
in-line, slice shows the karst features quite clearly (they are annotated with the red ellipses) but on the horizontal time slice they are not as clear. On Figure 14(b), the in-line slice shows the karst features more clearly than on the seismic display (again, they are annotated with the red ellipses) and on the horizontal time slice they are also much clearer.

Figure 15 shows the same set of composite slices (in the X, Y and Z directions) as in Figure 14, where Figure 15(a) again shows the original seismic survey and Figure 15(b) now shows the coherency results. On Figure 15(b), the in-line slice shows the karst features more clearly than on the seismic display (again, they are annotated with the red ellipses), but in a different way than the phase coherency result of Figure 14(b)/

**FRACTURED CARBONATE CASE STUDY**

Our second case study comes from a fractured carbonate reservoir in Alberta. The exact location of this reservoir cannot be revealed for reasons of confidentiality. Figure 16 shows a time slice of phase congruency through the main producing interval in the reservoir. There are two things to note on this time slice. First, the producing wells are shown as green circles on the slice. Notice the higher density of wells in the lower portion (southern part) of the map. In fact, there are only two producing wells in the top portion (northern part). Second, notice the high density of fractures in the southern part of the map that correspond very well to the high production. The fractures in the southern part of the map are aligned along a dominant east-west trend. Conversely, notice the lower density of fractures in the northern part of the map that correspond to lower production. Also, the fractures in the northern part of the map appear to be in conjugate sets, running both north-south and east-west. It is obvious from this map that the phase congruency algorithm has been able to identify fracture patterns that correspond to carbonate production.

Next, Figure 17 shows a vertical seismic section on the left along the result of analysis with three different algorithms: an un-named contractor section which attempts to display fracture density, phase congruency, and curvature. (Curvature is
an attribute that we have not discussed in this paper. For more details on curvature, see Roberts (2001)). On the three computed fracture plots an FMI, or Formation MicroImager, log curve has been superimposed, showing the density of fractures. Note that this log does not correlate well with the commercial product, but shows good correlation with both the phase congruency and curvature plots. In particular, the green colour indicates large values of both phase congruency and curvature in both plots and corresponds to large values of fracture density on the FMI log.

Finally, Figure 18 shows a plot of initial production (in cubic metres) versus amplitude of phase congruency, computed over six wells. As can be seen in this plot, there is a roughly linear trend between initial production and the amplitude of the phase congruency. In other words, higher phase congruency correlates with more fractures and more fractures correlates with more production.

CONCLUSIONS

In this study, we have implemented the phase congruency approach for identifying discontinuities on seismic data slices. As discussed, phase congruency has found application in the identification of features on photographic images and is used in image processing for robot vision. However, the method had seen little application to seismic data. We first described the theory of the phase congruency method, and then illustrated the method on a simple image consisting of an overlapping cylinder and cube. Finally, we applied the algorithm to two seismic examples, comparing the phase congruency results with other seismic techniques such as coherency and curvature.

In our first seismic example, a karst collapse study from the Boonsville field in Texas, we found that phase congruency did a good job in identifying these karst features. From an economic standpoint, the identification of the karst features was of great interest since it lead to the identification of compartmentalization within the reservoir interval above the karst collapse zones (Hardage et al., 1996).
Our second seismic example was a fractured carbonate reservoir from Alberta. We found that the phase congruency method was able to identify the areas in the field in which maximum fracturing had occurred. These areas of high fracturing in turn correlated with the highest initial production values in the field. When amplitude of phase congruency was plotted against initial production, a good correlation was found.

In this study, we found that other attributes such as coherency and curvature also performed well. However, the phase congruency method when applied to seismic slices gives a new and different seismic discontinuity attribute, one that can add value to ongoing seismic exploration and production efforts.
REFERENCES


Figure 1. The concept of phase congruency in 1D, where (a) shows that the individual terms in a Fourier series will be in-phase at a step, and (b) shows a polar plot of the real and imaginary Fourier terms used to compute phase congruency (from Kovesi, 2003).

Figure 2. A flowchart illustrating the basic steps in the phase congruency algorithm.
Figure 3. A simple test designed for the phase congruency algorithm, consisting of a cylinder of amplitude 2 intersecting a cube of amplitude 1, on a background of amplitude 0. The perspective view is in (a) and the map view is in (b).

Figure 4. The real component of the 2D Fourier transform of the image shown in Figure 3, where (a) shows the perspective view of the transform and (b) shows the map view.
Figure 5. Perspective views of the four log Gabor filters used in the phase congruency analysis of the image shown in Figure 3, for scales from 0 to 3, where \( m = 2.1 \) in Equation 2.

Figure 6. Map views of the four log Gabor filters used in the phase congruency analysis of the image shown in Figure 3, for scales from 0 to 3, where \( m = 2.1 \) in Equation 2.
Figure 7. Map views of the six angular filters used in the phase congruency analysis of the image shown in Figure 5(b), for angles from 0 to 150°.

Figure 8. Map views of all 24 combinations of radial and angular filters applied in this example, where (a) shows the filters at all angles for the first scale (Scale0), (b) shows the filters at all angles for the second scale (Scale1), (c) shows the filters at all angles for the third scale (Scale2), and (d) shows the filters at all angles for the last scale (Scale3).
Figure 9. Map views of the (a) original image consisting of a cylinder and a cube from figure 5(b), and (b) the final analysis using phase congruency. Notice the clear definition of the edges of the two objects.

Figure 10. A schematic showing the implementation of the phase congruency algorithm to seismic data.
Figure 11. A map showing the location of the Boonville gas field. (Hardage et al., 1996).

Figure 12. Inline 141 from the Boonville survey, where the red ellipses indicate the karst structures. The picked events are, from shallow to deep, Davis (green), Runaway (blue) and Vineyard (red).
Figure 13. A time structure map of the Davis formation over the Boonsville survey. The circular anomalies represent karst structures and the horizontal red line is the position of inline 141, shown in Figure 12.

Figure 14. A vertical slice showing karst features superimposed on a horizontal slice at 1080 ms, roughly halfway through the karst collapse, where (a) shows the seismic volume and (b) shows the phase congruency volume. The red ellipses on both figures illustrate the vertical collapse features.
Figure 15. A vertical slice showing karst features superimposed on a horizontal slice at 1080 ms, roughly halfway through the karst collapse, where (a) shows the seismic volume and (b) shows the coherency volume. As in Figure 15, the red ellipses on both figures illustrate the vertical collapse features.

Figure 16. A time slice of phase coherency within the reservoir interval of a carbonate reservoir in Alberta, where the green circles represent producing wells.
Figure 17. The seismic section on the left and, from left to right: a contractor section that computes fracture density, phase congruency and curvature. Superimposed on the three computed sections on the right is an FMI, or Formation MicroImager, log that measures fracture density.

Figure 18. A crossplot of initial production from the carbonate reservoir with phase congruency amplitude.