An Application of Optical Flow to Time-Lapse Analysis in 2-D Seismic Images

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Abstract

Time-lapse (4-D) seismic reservoir monitoring is a relative new technology that is gaining recognition in oil and gas producing areas around the world. In this paper, we propose an application of Horn-Schunck's optical flow estimation method in order to obtain the movement field between pairs of seismic images. Optical flow estimation can provide important information about velocity of each image pixel. This way, we show that is possible to catch important displacements between pairs of seismic images separated by a time interval. In this work, each seismic image was deformed through the application of a synthetic field. The results obtained show that this method is able to recover with reasonable precision tiny displacements commonly found in time-lapse seismic data.

Introduction

The use of time-lapse technologies in order to perform analysis and monitoring of the fluid and pressure in oil and gas producing areas has advanced rapidly in two last decades (Lumley, 2004). These technologies involve the process of taking several seismic surveys separated by a calendar interval, at same site, in order to image and detect important changes in a producing reservoir. If each seismic survey is formed by 3-D data, the extra dimension is calendar time. So, the set of these techniques are often termed "4-D seismic", and they are quickly becoming a very important engineering reservoir management tool, that can save hundred of million of dollars, when correctly applied (Lumley, 2001).

Although 4-D seismic techniques can provide an improved seismic monitoring, residual differences, that are independent of changes in the subsurface geology, may exist in the repeated time-lapse data. These residual differences add noise to the model and consequently impact the effectiveness of the method. So, it is important to ensure seismic repeatability in time-lapse seismic monitoring. A variety of factors are involved in the seismic repeatability study, such as the depth of buried detectors small variations in water table, tides, currents and temperature, ambient noise, transition zone, subsidence, source and geophone positions, source signatures, geometry design, and CMP stack fold distribution. Some of the non-repeatability problems can be solved by the careful deployment of source and receiver positions. However, problems such as those caused by annual near surface variations are more complicated to solve at the acquisition stage. Commonly, these problems can only be solved in the post-processing steps (Zhang and Schmitt, 2006).

There are several researches and study cases in seismic literature involving time-lapse techniques application in producing reservoirs. Van Gestel *et al.* (2008) present their experience in five years of continuous seismic monitoring of Vahal Field, located in the North Sea. The authors show that a combination of permanently installed seismic sensors and highly repeatable acquisition can provide high-quality 4-D images. These images can be used to improve reservoir model and help to plan and reduce risk when drilling new wells. Foster *et al.* (2008) present an overview of the status of BP's three ocean-bottom cables (OBC) monitoring systems and installation and operation of similar systems at Clair and ACG. OBC systems, in the way that they have been implemented in the three BP deployments, promise highly effective seismic monitoring data, providing both imaging quality and repeatability. Davies *et al.* (2008) shows that the use of permanent sensors deployed in the wellbore and along the tubing, in the surface production network and in the facilities provide a rich data flow to support advanced well and reservoir management techniques. Arts *et al.* (2004) present seismic interpretation of time-lapse seismic data provided by monitoring of CO_2 injection into a saline aquifer. The authors conclude that the effect of CO_2 on the seismic data is large in terms of seismic amplitude and in observed velocity pushdown effects.

A new alternative to detect time-lapse seismic effects is proposed by Matos *et al.* (2004). The authors use self organized maps (SOM) combined with wavelet transform to detect time-lapse changes. Wavelet transform is used in order to detect seismic traces singularities of each time-lapse 3-D cube. Then, these detected objects are classified using the clustering of SOM. The authors also show a successful application of this technique to the Troll West gas province, offshore Norway.

Claudino *et al.* (2008) examine the main effects of permeability barriers on seismic response using fluid flow simulations to generate pressure and saturation fields. The authors have performed several simulations in a simple reservoir model which has vertical and horizontal variations of porosity as well as permeability barriers. The authors use fluid substitution theory, Gassmann and patchy models, and Batzle and Wang's empirical relationship to model the main seismic parameters, such as acoustic impedance and compressional velocity. Synthetics seismograms and some contrast sections were generated to compare the seismic images prior and after fluid injection events in subsequent time periods to analyze possible differences in the seismic parameters due to changes in barriers properties. A methodology to examine barriers effects on seismic response is also proposed.

Hale (2007) presents a new method for estimating displacement vectors from time-lapse seismic images. The author uses a local phase-correlation instead of a local cross-correlation in order to improve features detection in seismic data. Furthermore, it is showed that a cyclic sequence of searches of correlation peaks constrained to one of the axis of the data can be a better strategy than searching directly for peaks in all data axis.

In computer vision, optical flow estimation is a key problem and consists of finding the motion of objects in a given sequence of images. Optical flow algorithms can generate an approximation of the local scene motion based upon local derivatives, in a given sequence of images. Optical flow may be used to perform motion detection, object segmentation, and time-to-collision and focus of expansion calculations, motion compensated encoding, and stereo disparity measurement (Beauchemin and Barron, 1995). There are several known methods for optical flow computation.

Horn and Schunck (1981) present a method that estimated image velocity field based on time-space derivatives. The method assumes small intervals between images, constant illumination and movement smoothness. An advantage of Horn-Schunck method is that it generates a high density of flow vectors. A negative point, is that it is more sensitive to noise than others methods.

Another popular method is proposed by Lucas and Kanade (1981). This method is a version of two-frame differential methods for motion estimation and can be used in combination with statistical methods to improve the performance in presence of outliers in noisy images. The solution as given by Lucas and Kanade is a non-iterative method, which assumes a locally constant flow. It is a very robust method in presence of noise. However, it does not generate high density vector fields.

McCane *et al.* (2001) present an evaluation of seven optical flow algorithms, using synthetic and real sequences. The authors present a test suite for benchmarking optical flow algorithms and propose that researchers should benchmark their algorithms using a standard test suite. Also, it is offered an Web site as a repository for standard sequences and results.

In this work, we propose the application of Horn-Schunck's optical flow estimation method in order to obtain the movement field between pairs of seismic images. Important seismic alterations can be observed by analyzing the movement field provided by optical flow computations. In this way, the use of optical flow methods in time-lapsed seismic data can provide a reasonable support in analysis and monitoring of producing areas.

Optical Flow

Optical flow (Beauchemin and Barron, 1995) can be defined as the pattern of apparent motion of objects, surfaces, and edges in a visual scene. It can be caused by the relative motion between an observer and the scene, or by the movement of the objects in scene. Through optical flow estimation techniques it is possible to recover the 2D velocity field, which describes the aparent movement in a pair of images.

Methods for optical flow computation can be divided into three main groups: differential techniques, techniques of correlation and frequency-based techniques (Barron *et al*, 1994). In these techniques, the initial hypotheses for the computation of optical flow are that the intensity between different frames in a sequence of images is approximately constant in a small time interval and the displacement will be minimal.

If we consider *I* (*x, y, t*) the intensity of the pixel located at position (*x, y*) at time *t*, it is assumed, by definition, that the time interval between two images is very small and the intensity is approximately constant (Figure 1).

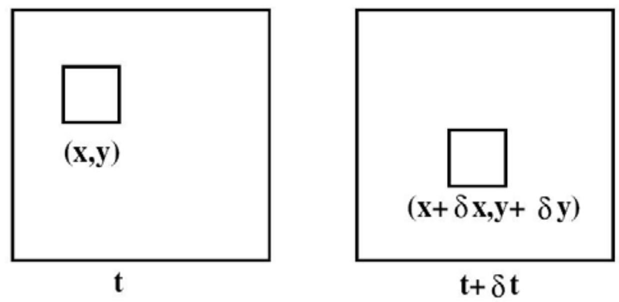

Figure 1: Image region at position (*x,y,t*) is the same as at ($x+\delta_x, y+\delta_y, t+\delta_t$) .

Thus, considering only small local translations, we can formulate a motion constraint expression, given by

$$I(x,y,t) = I(x+dx, y+dy, t+dt)\,. \quad (1)$$

Performing a 1st order Taylor series expansion about I (x, y, t) in Equation (1) and through some algebraic manipulations (Barron and Thacker, 2005), we obtain the following equation

$$\frac{\partial I}{\partial x}\frac{\partial x}{\partial t} + \frac{\partial I}{\partial y}\frac{\partial y}{\partial t} + \frac{\partial I}{\partial t} = 0\,. \quad (2)$$

But we know that $\bar{v} = \left(\frac{\partial x}{\partial t}, \frac{\partial y}{\partial t}\right)$ is the demanded velocity vector. Furthermore, $\nabla I = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right)$ is the gradient vector of the function in *x* and *y* directions. So, we can write Equation (2) more compactly as

$$\nabla I.\bar{v} + I_t = 0\,, \quad (3)$$

and this equation is known as Motion Constraint Equation.

However, only Equation (3) is not sufficient to estimate the components of velocity vector. This happens because the number of terms to be found is greater than the number of equations available.

Therefore, It is necessary to add other constraints to the model in order to find all velocity components. At this point, the methods of Lucas-Kanade and Horn-Schunck are commonly used in order to estimate the values of the velocity vector. In this work, we choose Horn-Schunck method in order to estimate 2-D velocity fields from pairs of seismic images.

Horn-Schunck Method

In order to simplify the process of motion field estimation, Horn-Shunck method assumes that incident light on the surface is uniform. It is also assumed that the reflection varies smoothly and there are not discontinuities in velocity flow. Thus, the model contains two constraints: the constant illumination constraint, which assumes that the total light is constant in both images and the smoothing constraint, which assumes that neighboring points have similar velocities.

In constant illumination constraint, if the illumination of an image point *(x, y)* in image plane at time *t* is described by *E (x, y, t)*, we can write the following equation

$$\frac{dE}{dt} = 0\,. \tag{4}$$

Applying the chain rule, we have

$$\frac{\partial E}{\partial x}\frac{dx}{dt} + \frac{\partial E}{\partial y}\frac{dy}{dt} + \frac{\partial E}{\partial t} = 0\,, \tag{5}$$

and $u = \frac{dx}{dt}$ and $v = \frac{dy}{dt}$ are the components of the demanded velocity vector, resulting on a single equation with two unknown terms, given by

$$E_x u + E_y v + E_t = 0\,. \tag{6}$$

Equation (6) expresses the same motion constraint given by Equation (3). So, at this point, Horn-Schunck method adds the smoothness constraint in order to find all unknown terms.

We know that if each point move independently, it would be almost impossible to recover the movement field. Thus, smoothness constraint indicates that neighboring points have similar velocities and the velocity varies smoothly in most of the velocity field. This constraint can be expressed mathematically by minimizing the square of the magnitude of the velocity gradient in both directions (Barron and Thacker, 2005).

The estimation of partial derivatives E_x, E_y and E_t is held by calculating the average of the first four adjacent regions of the pair of images, as follows

$$\begin{aligned} E_x = \frac{1}{4}(&img_1(i+1,j) + img_2(i+1,j) + img_1(i+1,j+1) + \\ &img_2(i+1,j+1) - img_1(i,j) - img_2(i,j) - \\ &img_1(i,j+1) - img_2(i,j+1)) \end{aligned}\,, \tag{7}$$

$$\begin{aligned} E_y = \frac{1}{4}(&img_1(i,j+1) + img_2(i,j+1) + img_1(i+1,j+1) + \\ &img_2(i+1,j+1) - img_1(i,j) - img_2(i,j) - \\ &img_1(i+1,j) - img_2(i+1,j)) \end{aligned}\,, \tag{8}$$

$$\begin{aligned} E_t = \frac{1}{4}(&img_2(i,j) + img_2(i,j+1) + img_2(i+1,j) + \\ &img_2(i+1,j+1) - img_1(i,j) - img_1(i,j+1) - \\ &img_1(i+1,j) - img_1(i+1,j+1)) \end{aligned}\,, \tag{9}$$

At this point, the problem becomes a minimization problem, and we must to find the values *u* and *v* that minimizes the following expression

$$\varepsilon_b = E_x u + E_y v + E_t\,, \tag{10}$$

with the smoothness constraint

$$\varepsilon_c^2 = \left(\frac{\partial u}{\partial x}\right)^2 + \left(\frac{\partial u}{\partial y}\right)^2 + \left(\frac{\partial y}{\partial x}\right)^2 \left(\frac{\partial y}{\partial y}\right)^2 \tag{11}$$

A direct solution of this minimization problem has a high computational cost, so it is necessary to try an iterative method (Barron and Thacker, 2005). In order to find the optical flow field (*u*, *v*) which minimizes the functional in Equation (12), we apply the Euler-Lagrange equation from variational calculus.

$$\varepsilon^2 = \iint (\alpha^2 \varepsilon_c^2 + \varepsilon_b^2)\,dxdy \tag{12}$$

Using the laplacian operator discretization we achieve a linear equations system which is commonly solved by the Gauss-Seidel method. At each iteration, new values for *u* and *v* can be obtained as follows

$$u^{n+1} = \bar{u}^n - E_x\left(\frac{E_x u + E_y v + E_t}{\alpha^2 + E_x^2 + E_y^2}\right) \tag{13}$$

$$v^{n+1} = \bar{v}^n - E_y\left(\frac{E_x u + E_y v + E_t}{\alpha^2 + E_x^2 + E_y^2}\right) \tag{14}$$

where $\bar{u}$ and $\bar{v}$ arose from the discretization of laplacian operator. The α weight factor is a parameter which can be used to emphasize the constant illumination constraint or the smoothing constraint. One can refer to Horn and Schunck (1981) for more details.

Accuracy Measures

The most common performance measure in optical flow literature is the angular error (AE) (Baker *et al*., 2007). The AE between two vectors (u_0, v_0) and (u_1, v_1) is the angle in 3-D space between *(u_0, v_0, 1.0)* and *(u_1, v_1, 1.0)*. Thus, the AE is usually computed by normalizing the vectors, taking the dot product, and then taking the inverse cosine of their dot product.

The goal of angular error is to provide a relative performance measure that avoids divisions by zero in case of null flows. In optical flow applications, the angular error is calculated between real field vectors and estimated field vectors and provides a good error measurement. In this work, we use the average angular error (AAE), i.e, the average among all angular errors at each image point in order to measure velocity field estimation performance.

Another measure often used is the error defined by

$$e = \sqrt{(u_0 - u_1)^2 + (v_0 - v_1)^2} \ , \quad (15)$$

which provides a more absolute accuracy measure between real and estimated vectors (Baker *et al.*, 2007). The average of this measure calculated using each pair of vectors (real and estimated) was used as a performance criterion in this work.

Results

Seismic data used in this work correspond to 7 sections (slices) of a real 3-D seismic volume (Figure 2). The deformation of each slice was made from a synthetic radial deformation, in which all the vectors tend to point to the center of the image, as shown in Figure 3. Bilinear interpolation was used in order to reconstruct deformed image signal.

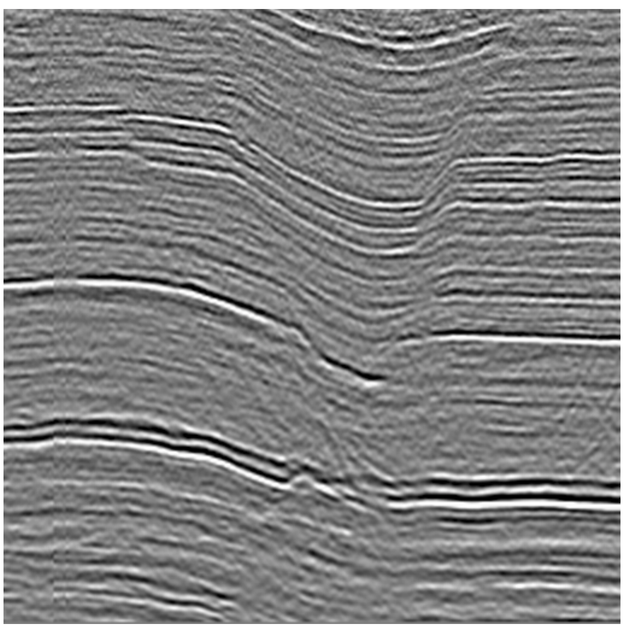

Figure 2: Example of seismic image used in this work.

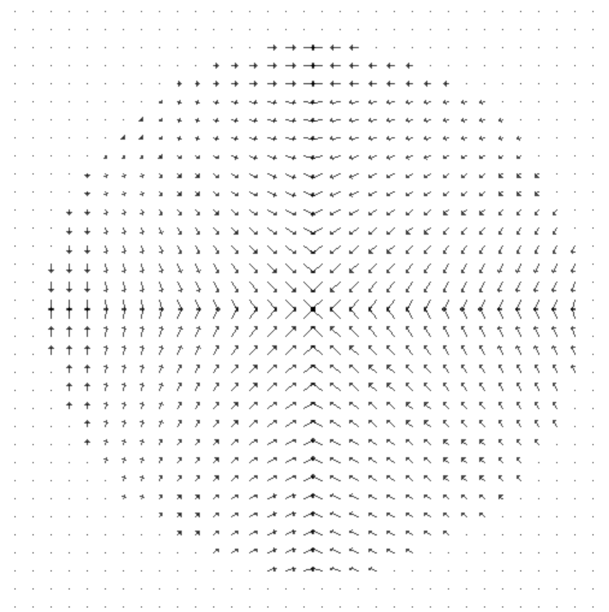

Figure 3: Radial distortion field applied in each seismic image in order to measure optical flow motion estimation performance.

We apply tests varying the value of alpha parameter and the maximum size that each velocity component can reach, in pixels units. Several values were tested for the parameter alpha, ranging from 1 to 64, and the best value found was 32. Each displacement vector component can have size of 0.1, 0.5, 1.0, 2.5, 4.0 and 5.0 pixels units.

Figure 4 shows an estimated field for a pair of images of dataset. The maximum displacement component is 1.0 pixel.

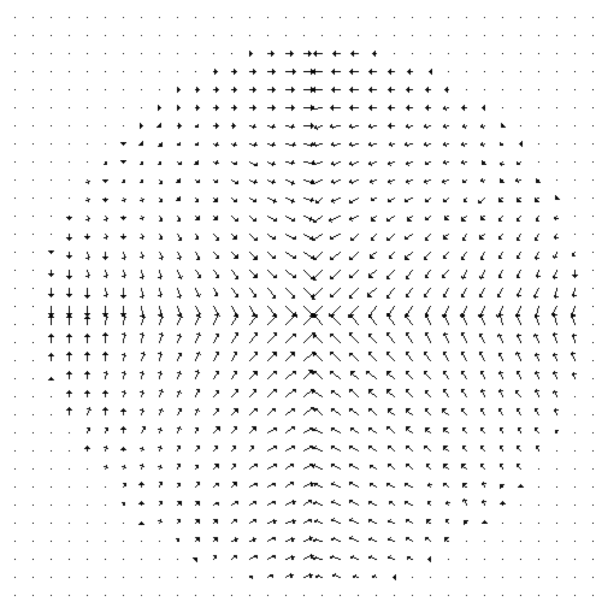

Figure 4: Example of estimated velocity provided by Horn-Shunck method

The number of iterations performed in each test was 400. The average time to process each pair of images was 10s on a 2.4 GHz processor with 2.0 GB of RAM.

Table 1 summarizes the results obtained by application of Horn-Schunck method in seismic images. The average errors shown are calculated by the sum of the average error of each processed image, divided by the value *n* = 7, which is the total number of images available.

Maximum component size	AAE/*n*	Average Error/*n*
0.1	0.9672	0.0170
0.5	2.6313	0.0509
1.0	3.0340	0.0724
2.5	4.21140	0.2217
4.0	9.9488	0.7658
5.0	18.7389	1.4347

Table 1: Average results for alpha=32 and maximum vector component size ranging from 0.1 to 5.0.

For small displacements, which are commonly found in seismic data, these results indicate that the method has reasonable performance, with average angular error of a few degrees. As the displacement increases, however, this error will increase, and this fact implies that for vector displacements whose components are larger than 4, the method does not present good performance.

Conclusions and Future Works

The use of new tools able to perform time-lapse seismic reservoir monitoring is growing in acceptance in recent years. The wide acceptance of the use of 4-D seismic analysis for petroleum industry is evidenced by the large number of recent publications in major conferences and journals in the area who witnessed cases of geophysical successful application of such technologies.

Based on the observed results, we conclude that optical techniques, such Horn-Schunck method can be applied in 4-D analysis in order to recover displacement vectors with a reasonable accuracy even in small magnitude vector fields. The results showed that for displacements of the order of sub-pixels, commonly found in seismic data, the method is able to estimate the optical flow with a reasonable error. In order to better assess the methodology, however, further investigations are necessary, such as the use of seismic data with fields of natural displacements. For future work is to realize the extent of the implementation of the Horn-Schunck algorithm for 3-D seismic data and the implementation of other known techniques to estimate optical flow, such as variational techniques.

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