Computers & Geosciences 41 (2012) 40–46

Contents lists available at SciVerse ScienceDirect

Computers & Geosciences

journal homepage: www.elsevier.com/locate/cageo

Stress inversion using slip tendency

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ARTICLE INFO

Article history:
Received 18 March 2011
Received in revised form
29 June 2011
Accepted 1 August 2011
Available online 22 August 2011

Keywords:
Structural geology
Stress inversion
Slip tendency
Stress tensor

ABSTRACT

The in situ stress state is an important controlling factor for the slip behavior of faults and fractures in the earth's crust and hence for the productivity of faulted and fractured hydrocarbon reservoirs. Current methods for stress tensor estimation rely on slip vector field data; however, this information is not generally available from data sets that are commonly used in the oil and gas industry. This work presents a new stress inversion approach where slip tendency is used as a proxy for fault displacement, which can easily be extracted from data sets routinely used by the oil and gas industry. The inversion approach is demonstrated using a data set obtained from the Canyon Lake Gorge in Comal County, Texas.

1. Introduction

Faults and fractures provide important pathways for subsurface fluid flow in many geologic settings including aquifers (Ferrill et al., 1999), geothermal reservoirs (Moeck et al., 2009), and hydrocarbon reservoirs (Ameen, 2003). They act as both conduits for and barriers to flow (Caine et al., 1996) and are therefore the primary structural determinants of aquifer and reservoir compartmentalization. In situ crustal stresses, because they control the slip behavior of faults and fractures (e.g., Barton et al., 1995; Ferrill et al., 1999), also exert an important control on the fluid conductivity of faulted and fractured systems. Uncertain or poorly constrained estimates of stress states can lead to high risk both in energy exploration and production, and in the estimation of recoverable reserves.

Several methods exist for the indirect determination (inversion) of the stress tensor based on observed effects of that stress tensor using data sources such as earthquake focal mechanisms (Gephart and Forsyth, 1984), paleostress indicators (Angelier, 1979, 1984), and microseismicity—when the data set contains slip vector information (Tezuka and Niitsuma, 2000). All these methods rely on knowledge of the slip vector field generated by the stress state being sought (see Blenkinsop et al., 2006, for a review). However, slip vector information is not generally available from such data sets as seismic reflection data (Orife et al., 2002) and the microseismic swarms commonly used in the oil and gas industry.

In this paper we develop a stress inversion technique based on slip tendency analysis, which allows estimation of the stress state using fault displacement data (as distinct from slip vector information), which can easily be extracted from data sets routinely used by the oil and gas industry. This method can provide practitioners with a reasonable estimate of the stress tensor, or at least a starting point, from which additional pieces of information, such as expert knowledge, can be used to fine tune the estimate (the methodology described in Sections 3 and 4 and Appendix A represents patent pending technology). Analysis of the effects of in situ stresses on existing faults and fractures is an extremely important key factor in optimization of hydrocarbon production from fractured reservoirs, design and interpretation of "hydrofracs" to stimulate hydrocarbon production, design and operation of fractured rock geothermal fields, and prediction of the effects of underground CO_2 sequestration. In addition to the fault and fracture network, the in situ stresses are key inputs to this analysis.

Section 2 provides an overview of slip tendency analysis, which is the physical basis for the proposed inversion approach. Section 3 presents the proposed comparison metric, which forms the mathematical basis for the inversion approach: this metric allows the quality of a candidate stress tensor to be quantified based on agreement between predicted slip tendency and observed slip magnitude for a set of measured surfaces. The mathematical representation of the stress tensor for the purpose of stress inversion is discussed in Section 4. Section 5 describes a Bayesian approach for quantifying the statistical uncertainty in the solution. Finally, Section 7 presents an illustrative example of stress inversion using field data obtained from the Canyon Lake Spillway Gorge in Comal County, Texas.

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doi:10.1016/j.cageo.2011.08.004

2. Slip tendency analysis

Slip tendency analysis is based on the premise that the resolved shear and normal stresses on a surface are strong predictors of both the likelihood and direction of slip on that surface (Morris et al., 1996). The method has been used successfully to characterize fault slip (Streit and Hillis, 2004) and fault slip directions (Lisle and Srivastava, 2004; Collettini and Trippetta, 2007). Fractures in high-slip-tendency orientations are, in many cases, better flow conduits than fractures in low-slip-tendency orientations (Barton et al., 1995; Morris et al., 1996; Ferrill et al., 1999; Sibson, 2000). The effect of stress anisotropy is greatest when the effective stress conditions on a fault or fracture approach those required for slip: the so-called critical stress (Stock et al., 1985; Wiprut and Zoback, 2002; Zhang et al., 2007). Thus, preferential fluid flow through fault and fracture pathways is more pronounced the greater the differential stress and the greater the area of faults and fractures experiencing high slip tendency (Zoback et al., 1996; Morris et al., 1996; Ferrill et al., 1999; Takatoshi and Kazuo, 2003).

Formally, the slip tendency (T_s) of a surface is defined as the ratio of shear stress (τ) to normal stress (σ_n) on that surface (Morris et al., 1996):

$$T_s = \tau/\sigma_n. \tag{1}$$

The slip tendency is only a function of the stress tensor and the orientation of the surface. Whether or not slip occurs will depend on the coefficient of static friction (e.g., Byerlee, 1978). For a cohesionless surface, slip occurs when the slip tendency exceeds the coefficient of static friction. In addition, the magnitude of the effective intermediate principal stress (σ_2') relative to the effective maximum and minimum principal stresses has a profound influence on the slip tendency pattern (De Paola et al., 2007; Morris and Ferrill, 2009).

3. Definition of a comparison metric

The basic premise of this work is that slip tendency can be used as a proxy for actual fault displacement, and that fault displacement can be very broadly defined. For example, in the case where mapping of seismic reflection data permits the characterization of fault gaps or overlaps (sometimes referred to as fault polygons), the fault gap can be represented by a surface consisting of triangular patches. The areas of these patches can be used as a proxy for displacement. Our approach obviates the need for slip vector information for inversion. This allows evaluation of the quality of a candidate stress tensor based on the degree of agreement between the slip tendency values and the corresponding measured displacement values for a set of observed surfaces. Stress inversion is then a matter of searching for the stress state that optimizes this measure of agreement. The inverted stress tensor will be the tensor that best fits the input fault displacement data. Thus the tensor will be an estimate of current in situ stress if the faults are still active; for example, if they are seismically active, offset the earth's surface, or are a representation of microseismic data. In other cases the tensor will represent the paleostress state at the time of formation of the faults.

There are two basic criteria that we consider in developing a metric that quantifies the goodness of fit of a stress tensor based on agreement between slip tendency and observed displacement at measured surfaces:

1. We expect a positive relationship between slip tendency and displacement.
2. Small displacements with large slip tendency are more plausible than large displacements with small slip tendency.

The first criterion is self-explanatory, while the second is included to account for the fact that the surfaces may have started slipping at different points in time. This suggests that a surface with a high-slip-tendency orientation could have either a large actual displacement (started slipping early) or a small actual displacement (started slipping late). However, a surface with a low-slip-tendency orientation should have little or no actual displacement. Therefore, stress states that imply low slip tendencies on surfaces that have large displacements are less likely to be good solutions than stress states that imply high slip tendencies on surfaces that have small displacements.

For coherent data sets with a large number of observed surfaces, these two criteria alone should be sufficient to develop a meaningful stress inversion process. A potential problem could arise, however, if the set of measured surfaces did not sufficiently cover the spectrum of possible surface orientations. For example, there may be few or no measurements for surfaces with orientations that are not conducive to slip. If the inversion algorithm were only presented with the measured data, it would have no information to guide it away from stress states that result in high slip tendencies for these surface orientations.

To address this problem, we introduce the concept of *zero-displacement artificial data*. Simply put, the set of measured surfaces can be augmented with artificial surface orientation data that are intended to represent surfaces showing no displacement. These artificial data could be generated based on knowledge of the structural geology, or they could be generated automatically based on an algorithm that tries to "fill in the gaps" in a given data set. Appendix A describes an algorithm for generating such artificial surface data automatically.

To formulate the comparison metric itself, we introduce normalized quantities for the measured displacement and the slip tendency. Denote measured surface displacement by s_m and slip tendency by T_s. The corresponding normalized values will be denoted by $\bar{s}_m$ and $\bar{T}_s$, respectively. These quantities will be constructed so that a value of one in each case corresponds to the highest expected level of slip, and zero corresponds to no slip.

This allows the normalized quantities to be directly compared. We begin by formulating the comparison function in terms of an error or penalty, ε, that is assigned for each case where a slip tendency is compared to a measured displacement. We propose the following error measure:

$$\varepsilon = \begin{cases} 2\times(\bar{s}_m - \bar{T}_s) & \text{if } \bar{s}_m > \bar{T}_s, \\ 2\times T_s^2 & \text{if } \bar{s}_m = 0, \\ -0.5\times(\bar{s}_m - \bar{T}_s)^2 & \text{otherwise}. \end{cases} \tag{2}$$

The basis for Eq. (2) is that the ideal state is that in which each normalized displacement measurement ($\bar{s}_m$) equals the corresponding normalized prediction ($\bar{T}_s$): in these cases the corresponding penalty or error measure is zero. Deviations from this ideal state are penalized based on whether the actual displacement is more or less than that predicted by the model, and the artificial zero-displacement data points are treated specially. If the actual displacement is more than predicted (the first case in Eq. (2)), the penalty is more severe, and if the actual displacement is less than predicted (the third case), the penalty is less severe. The second case treats the artificial zero-displacement surfaces by encouraging the corresponding slip tendency to go to zero.

Different normalization procedures are possible, but we have obtained reasonable results using the approach

$$\bar{s}_m = \frac{s_m}{s_m^{max}} \tag{3}$$

and

$$\bar{T}_s = \frac{T_s - T_s^{min}}{T_s^{max} - T_s^{min}}, \tag{4}$$