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The Effect of Velocity Uncertainty and Attenuation on Flow Estimates From Microseismicity

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Summary

We study the effects of the velocity uncertainty and attenuation in the subsurface on the fluid pressure diffusivity estimated from observed microseismicity. We use a probabilistic physical model that directly ties fluid pressure in the subsurface during the injection to direct-arrival times of induced microseismic events observed at the monitoring receiver array to track the propagation of uncertainty in the forward model and inversion. We estimate the fluid pressure due to the injection, and quantify the uncertainty of this estimate, from synthetically modeled noisy travel times. The errors in the estimated travel times are primarily due to a combination of an uncertain velocity model and attenuation. Our examples demonstrate that the robust inversion of fluid flow parameters from microseismic data is possible if all effects contributing to uncertainty are properly accounted for.

Introduction

A good understanding of the fracture system created as a result of hydraulic fracturing is key to accurate production estimates, planning future fracturing jobs, and ultimately quantifying business risks. Microseismic monitoring remains one of the primary methods of monitoring hydraulic fracturing in the subsurface. In order to clearly demonstrate the value of microseismic monitoring, uncovering the relationship between the fluid flow in the subsurface and the recorded microseismic data is necessary.

We have developed a physical probabilistic model that ties the increase in fluid pressure in the subsurface due to the fluid injection to the observed microseismicity, i.e., arrival times from induced microseismic events. This simple model includes descriptions of key physical processes, such as fluid flow, rock failure and creation of microseismic events, seismic wave propagation from the fracture zone to the receiver array, and the recording of seismic signals. Several dominant factors control induced rock failure and seismic wave propagation, e.g., rock cohesion, rock friction, maximum and minimum stresses in the formation, velocity model and attenuation. Knowledge of all of these quantities is necessary to predict the microseismicity induced by the injected fluid.

In practice, these quantities are not known exactly but estimated with uncertainty from various measurements. Given these parameters with their associated uncertainties, we can predict and describe statistically general patterns of induced microseismicity, including likely event locations and origin times, and hence distributions of arrival times of events recorded at the receiver array. We use Bayesian inference to formulate the inverse problem of estimating the fluid flow diffusivity from observed microseismic event arrival times. Generally speaking, recorded arrival times along with velocity model and attenuation models are used to estimate the event locations and origin times, which are in turn used to invert for the diffusivity. Because we constantly track uncertainty in all parameters, the result is not a deterministic estimate of the fluid flow parameters but a statistical distribution that describes probabilities of all fluid flow models consistent with the recorded data.

Our framework is general and applicable to various fluid models, rock failure models, and seismic propagation models. In this paper for illustration purposes we use a simple model to specifically study the effect of the velocity uncertainty and attenuation on the recorded arrival times.

It is well known that both uncertainty in the velocity model and attenuation have profound effects on reconstructed event locations and origin times. Our goal is to show that despite these negative effects, fluid flow can still be estimated from microseismic data under favorable circumstances. We show with numerical examples that obtaining robust estimates of the parameters controlling fluid flow is possible if all contributing factors are properly accounted for. Ignoring an important source of uncertainty, such as attenuation, may lead to biased inversion results.

Diffusive flow

We describe the forward model that ties the fluid flow to the observed microseismic data. We first consider a two-dimensional radially symmetric medium around the injection point (Shapiro et al., 2005).

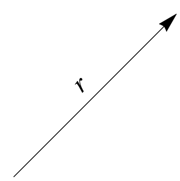

Figure 1. Radially symmetric medium.

We model the fluid pressure in the subsurface as an effective diffusion. This effective diffusion is different from matrix diffusion. In a fractured medium fluid may diffuse at a large scale through many connected fractures regardless of the permeability of the rock matrix (Shapiro et al., 2000). The diffusion equation that governs the fluid pressure is written as

$$\partial p(r,t)/\partial t = \nabla\cdot[\alpha(r)\nabla p(r,t)]+R(r,t),$$

where $\alpha(r)$ is the fluid pressure diffusivity, and $R(r,t)$ is the injection rate.

Rock Failure

We use the classical laboratory-validated Mohr-Coulomb theory to model rock fracture due to the increased fluid pressure. The medium is described with a set of four mechanical parameters. At each distance from the injection point, r_i , the medium can be described by four parameters that control rock failure:

$$m_i = \{\sigma_c(i), \kappa(i), \sigma_1(i), \sigma_3(i)\},$$

where σ_c is the rock cohesion, κ is the rock friction, σ_1 is the maximum principal stress, and σ_3 is the minimum principal stress (Ottosen and Ristinmaa, 2005). These parameters are assumed to be statistically independent at different locations.

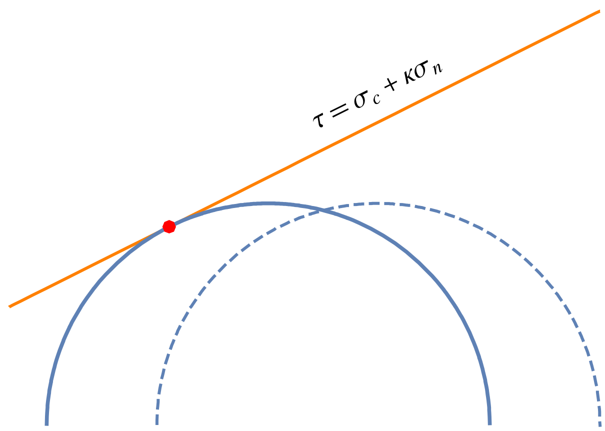

Figure 2. Mohr-Coulomb failure criterion.

Increasing the fluid pressure by injecting fluid reduces the effective stress. If the pressure reaches a critical value $p_{fail}(i)$, then the rock fractures at the corresponding location, and a seismic event is created. If all four parameters of the formation are known exactly at all locations, and if the injection is accurately described, then the pressure increase in the formation can be numerically calculated, as can be the locations and times of all rock fractures and seismic events. If the four parameters, $\{\sigma_c, \kappa, \sigma_1, \sigma_3\}$, carry uncertainty then rock failures may or may not occur depending on how strong the rock is at a given location. Poliannikov et al., (2015) describe a method for calculating the probability of a failure at any given location, ***)*** $P_{fail}(r_i \mid \alpha)$, and the distribution of the time of the failure, $f_{tfail(ri|\alpha)}(t_i)$.

Seismic Wave Propagation

Each seismic event emits a wave that propagates in a true physical (but generally unknown) velocity model to the receiver array, where individual phases are picked with some picking error. If the uncertainty in the velocity model and the errors in the picking algorithm are estimated or assumed then we can construct probability distributions for the arrival times for all of the microseismic events at the receiver array.

The largest contributor to the uncertainty in the predicted travel times is the assumed velocity model. Significant efforts are undertaken to obtain good velocity models; however, it is widely accepted that resulting velocity models are not exact and carry significant uncertainty. This clearly poses a potential problem for inversion if the assumed velocity model significantly deviates from the true velocity model.

Although in this paper we deal with arrival times only, setting aside amplitude information, attenuation also plays an important role here. If the velocity model is dispersive, higher frequencies may travel faster than lower frequencies (Cole and Cole, 1941). When higher frequencies are attenuated, the apparent velocity becomes lower; alternatively, arrivals are systematically picked later than they would be in the absence of attenuation. This clearly can lead to erroneously located events and therefore cause problems with using microseismic data for the purposes of the inversion for the diffusivity.

Probabilistic Inversion

If the event locations and origin times are known, then the diffusivity, α, can be inverted from these events as follows:

$$f(\alpha \mid s) \propto \Pi_i\, f_{tfail(ri|\alpha)}(t_i)\, P_{fail}(r_i \mid \alpha),$$

where

- $f(\alpha \mid s)$ is the posterior distribution of the diffusivity given all observed microseismicity summarily denoted as s;
- $P_{fail}(r_i \mid \alpha)$ is the probability of rock failure at a given location;
- $f_{tfail(ri|\alpha)}(t_i)$ is the probability density of the time of failure.

Informally, the posterior $f(\alpha \mid s)$ evaluates the likelihood that flow through the formation with a given diffusivity α is likely to produce microseismic events at given locations with given origin times.

Because the locations and origin times of microseismic events are not observed directly, they are estimated with some uncertainty from arrival times. Poliannikov et al., (2013, 2014) discuss a method for simultaneously locating and estimating origin times of all recorded events, *s*, and quantifying the associated uncertainty, from noisy time picks, *T,* and an uncertain velocity model. The output of their algorithm is the posterior distribution, $f(s \mid T)$, of all locations and origin times of microseismic events given noisy arrival time picks.

In order to invert for the diffusivity using microseismic time picks, we simply combine the two posteriors in a straightforward manner:

$$f(\alpha|T) = \int f(s|T)\, f(\alpha|s)\, ds,$$

The inversion works as follows. Observed time picks and an assumed velocity model, along with the associated uncertainties, are used to construct a joint distribution of event locations and origin times that are consistent with the picked arrival times. Possible realizations of a microseismicity catalog are then produced from this distribution. The probability of a diffusivity α is higher if a particular realization of microseismicity (both locations and origin times) is consistent with the flow that corresponds to diffusivity α.

Numerical examples

We simulate a fluid injection in the subsurface that causes induced microseismicity as shown in Figure 3.

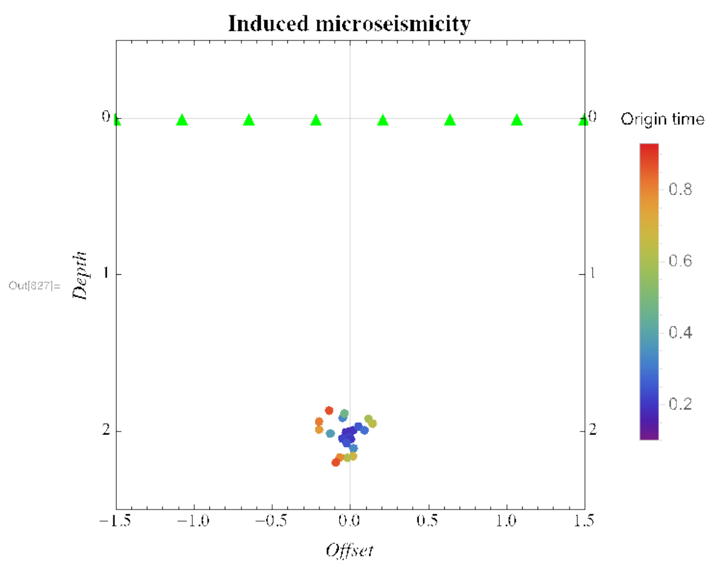

Figure 3. A simulated realization of the induced microseismicity caused by a fluid injection into a homogeneous isotropic medium with diffusivity α =1. Each event is recorded by a receiver array installed at the surface.

The true diffusivity is assumed to be $\alpha=1.0$. The minimum stress is assumed to be known up to an error of 10%. Figure 4 shows the result of the inversion when the velocity model is estimated with an error of up to 5%. We see that the true value for the diffusivity ($\alpha=1.0$) has a high probability, and we can also recover the uncertainty around this value.

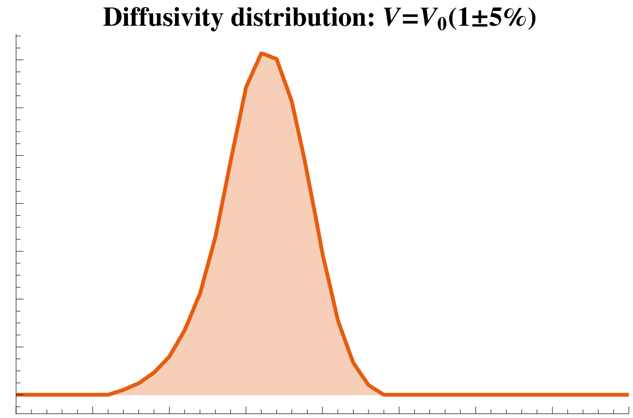

Figure 4. *The posterior distribution of the diffusivity,* α*, given observed noisy travel times and an uncertain velocity model. The velocity model is homogeneous with an error of ±5%.*

Figure 5 shows the result of the inversion when the velocity is consistently underestimated by 5-10%. We choose the lower velocity to simply model the effects of attenuation. Because we perform the inversion using incorrect assumptions, i.e., the true velocity model is not within the range of assumed velocity models, the true diffusivity cannot be accurately recovered. Using incorrect velocities results in mislocations for all events and erroneous estimation of their origin times. Because the diffusivity is ultimately estimated from event locations and origin times, a systematic bias in the velocity results in a systematic bias in the estimated diffusivity. This example underscores the importance of properly described uncertainty that is present in the model. When the true model is effectively ruled out by prior assumptions, accurate inversion cannot be expected.

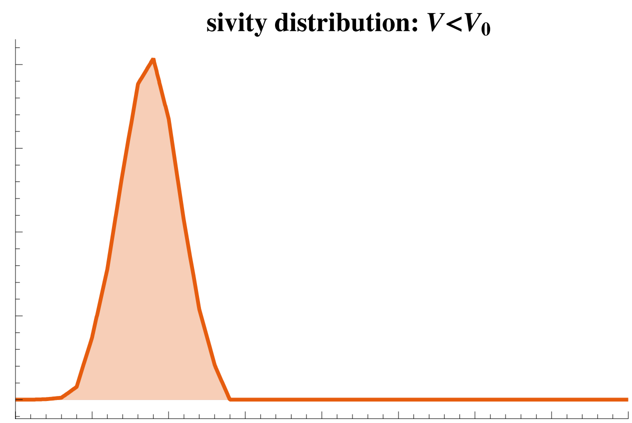

Figure 5. The posterior distribution of the diffusivity, α*, given observed noisy travel times and an uncertain velocity model. The velocity model is underestimated by 5-10%, e.g., as a result of the attenuation that was not properly accounted for.*

Conclusions

In this paper we presented a model that physically relates increased fluid pressure during injection to observed uncertain direct arrival times of the induced microseismic events. Our emphasis was on the effect of the seismic velocity model uncertainty and attenuation on the results of the inversion. Both velocity model uncertainty and attenuation may cause biases in the travel times that will affect estimates of event locations and origin times. These errors will then propagate to the inversion of the diffusivity. With simple numerical examples, we demonstrated that if the uncertainty in the assumed velocity model, explicit or due to attenuation, is properly accounted for then we can obtain reliable estimates of the fluid flow diffusivity. Failure to account for these effects properly may lead to biased results.

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