Meeting the challenge of uncertainty in surface microseismic monitoring

Mike Mueller* discusses the essential elements of today's successful microseismic monitoring surveys used in hydraulic fracturing operations during shale oil and gas resource exploitation, and looks ahead to the major challenge of uncertainty estimation and how it can be met.

It is over 10 years since a pioneering method for field-wide surface and near-surface microseismic data acquisition was first proposed as a solution to monitoring the intensive hydraulic fracturing operations required in the exploitation of unconventional hydrocarbons deposits, such as the shale plays of the United States. Since then the benefits of real-time 'frac mapping' for optimizing production, e.g., better well placement and stimulation strategies, have been widely acknowledged. In addition, the data can contribute continuously updated intelligence on potential environmental impact issues.

Although microseismic monitoring in unconventional resource plays is now being implemented in countries all around the world, documentation of the necessary elements for successful operations is still relatively scarce. If the results possible from this technology are going to win increased adoption in the industry, then the capabilities and limitations of current downhole, surface, and near-surface recording, data processing, and imaging applications need to be recognized with a roadmap for future developments.

This paper takes as its starting point consideration of the rationale for monitoring surveys, and then sets out a baseline for effective acquisition and interpretation of microseismic data. It then goes on to review one of the outstanding challenges for the further advance of the technology: how to quantify uncertainty in the detection of microseismic events and their estimated location. Arguably in the technical field with its emphasis on definitive solutions, we are insufficiently accustomed to incorporating uncertainty estimates into our workflows. There is something of an analogy with the popular work of the statistician Nate Silver, who almost uniquely correctly predicted the result of the last two US Presidential Elections. In his book 'The Signal and the Noise', he investigates how we can distinguish a true signal from a universe of noisy data in social contexts as varied as baseball, elections, and the stock market. In many cases unrealized assumptions and overconfidence account for failure. The lesson is that if our appreciation of uncertainty improves, paradoxically our predictions can get better too.

For microseismic data, interpretation workflows involve raw pointsets which contain both false positive and true positive candidate events. These are culled to determine predominantly true positive microseismic pointsets that can become the inputs for modelling microseismic-based discrete fracture networks and calculating stimulated rock volumes.

In general terms, the uncertainty of estimates is driven primarily by the noise itself, the array geometry, the earth model, and the choice of imaging method employed (Thornton, 2013). In this paper it is proposed that estimation theory may provide an important contribution to improving confidence in microseismic monitoring data.

To give an example, signal-to-noise ratio (SNR) is one key indicator of the uncertainty in migration-based imaging of those microseismic events. Thornton and Eisner (2011) suggest that reliability in terms of the ability to detect the complete set of events is a nearly binary function of SNR. Events above a threshold of 2.5–3 can easily be detected with a high probability of being correctly identified as 'true positives' but those below can be missed. The same principle applies to positional uncertainties. While vertical uncertainties are more sensitive to noise, both horizontal and vertical uncertainties decrease rapidly with increasing SNR.

Before highlighting further the possibilities of estimation theory, we need to understand that the relationship of recording geometry, imaging capability, and interpretation workflows will establish the ground rules for high confidence applications in areas such as stress characterization and response to stimulation, drainage/depletion constraints, and production estimates, hopefully leading to multi-disciplinary interest and expanded utilization.

Acquisition methods

The application of microseismic monitoring for oil and gas activities grew out of earthquake seismology during the pre- 'shale gale' era. This first microseismic monitoring predominantly utilized downhole, limited aperture, limited sensor-count arrays and classic P and S arrival picking, together with particle motion analysis to determine distance and direction from an event to the observation well's array (Warpinski, et al., 2012). Since the explosion in

* *MicroSeismic, Houston. E-mail: mmueller@microseismic.com*

© 2013 EAGE www.firstbreak.org

unconventional shale play developments since 2000, interest in microseismic monitoring has grown rapidly. The growing number of applications and variety of project conditions, along with location and budget constraints on drilling observation wells, motivated the development of surface and near-surface monitoring options (Duncan and Eisner, 2010). The enabling technology for these methods is imaging which requires acquisition geometries akin to those developed in active seismic applications.

Downhole
The downhole acquisition geometry is the legacy microseismic monitoring geometry as applied in oil and gas operations. Typically deployed in a single observation well, the receiving array consists of 8–40+ levels of three-component sensors deployed from just above the interval to be stimulated upwards if in a vertical observation well, and within the set of horizontal boreholes in a multi-lateral, pad drilling development. The downhole technique utilizes both P and S arrivals, along with particle motions to determine distance and direction to a candidate microseismic event. Proximity of the microseismic activity to the observation wellbore is key to high quality, low positional uncertainty microseismic imaging. Increasingly, the use of multiple observation wells is recognized as a means to lower positional uncertainty and possibly characterize rock failure modes (Sarkar, et al., 2012).

Surface and near-surface
Surface and near-surface acquisition geometries emerged after 2000 in response to the need for non-borehole based methods in hydro-fracturing applications as well as to extend microseismic monitoring to reservoir applications such as depletion and stress change monitoring during production (Duncan and Eisner, 2010). In contrast to the downhole geometry approach, close proximity to the microseismic activity is obviated and replaced by imaging inside the surface or near-surface footprint with wide-azimuth, high-fold, and large aperture seismic deployments. SNR becomes the primary event attribute for determining high quality, low positional uncertainty, true positive event selection (Thornton and Eisner, 2011). Such systems can be aerially extensive allowing for laterally consistent positional uncertainty over great distances enabling pad to field-wide microseismic applications with one installation.

Downhole and surface comparison
Downhole and surface acquisition approaches allow for complimentary applications but also introduce several challenges for direct comparison. These challenges include differences in wave propagation, frequencies, event-sensor distance, and processing methodology. Several of the comparison considerations are summarized in Table 1.

Downhole	Surface/near-surface
1D or multi-1D	2D
Borehole access	Surface access
Horizontal propagation	Vertical propagation
Proximal – great detail	Distant – extended volume
Detection to ~-3.0	Detection to ~-2.5
Well to pad scale	Well to field scale
10s of sensors; 3C	100s to 1000s of sensors; 1,3C
Frequency 15-200+Hz	Frequency 10-70Hz
Break picking, particle motion, limited imaging	Signal processing, imaging, stacking
Multi-mode (P and S)	Single-mode (1C) Multi-mode (3C)

Table 1 A comparison of several factors inherent in downhole and surface/near-surface acquisition geometries.

Interpretation issues
The interpretation of microseismic hypocentres includes several issues which cross seismological to processing to application factors. Understanding these interpretation factors should lead to improved application development.

Tensile/shear failure
For the vast majority of microseismic monitoring geometries tensile breakage of rock undergoing stimulation is too seismically weak to be detected. The ability to detect tensile events requires extremely close proximity and high SNR events. The vast majority of microseismic events available from either downhole or surface/near-surface geometries are due to shear motions which result in higher strength signals. Resolving these source mechanisms requires appropriate wavefield sampling necessitating multiple observation wells or wide-azimuth, high-fold, large aperture surface acquisition systems.

Microseismic 'fractures'
The language ubiquitously used in microseismic applications equates microseismic events with fractures. This is interpretive in its nature. The observed event is the result of some type of breakage or slippage in the rock mass as a result of the change in stresses from the introduction of high volumes of stimulation fluids and proppants or from the drawdown of fluids during production.

Hypocentre positional uncertainty
The uncertainty in position of each microseismic hypocentre is not routinely presented. However, this attribute of microseismic monitoring has a first order impact on virtually all applications. For downhole geometries, the

www.firstbreak.org © 2013 EAGE

positional uncertainty is related to event SNR and proximity to the observation well. For surface/near-surface geometries the positional uncertainty is related to event SNR. Both geometries critically depend on calibration of known events prior to imaging of events due to hydro-fracturing activities or fluid drawdown.

Pointset event count

It is almost universal in microseismic applications to witness an emphasis on event count as a factor in assessing a project's success. This thinking encourages the inclusion of many events in a pointset that are of weak signal strength, low SNR, or possessing other false-positive attributes. In evaluating hydro-fracturing applications the most important characteristics of a pointset are its overall geometry – length, width, height, along with event source mechanisms and patterns such as linearity or 'cloudiness' of the pointset.

Pointset surprises

A direct consequence of applying microseismic monitoring to hydro-fracture activities is the observation of pointset behaviours such as relatively long distance lineations and other event accumulations separated from the stimulated well. Commonly these features may be interpreted as previously unrecognized, sub-seismic fault or thoroughgoing fractures. Such unexpected features are routinely seen in all settings, but can be particularly prevalent in tectonic regimes. With the emergence of aerially extensive surface and near-surface acquisition systems, recognition of these geologic features is increasing. Such features can have a significant effect on the effectiveness of a stimulation programme, and recognition and mapping of them can provide for informed mitigation.

False positives / true positives

Both downhole and surface microseismic methods involve interpretative procedures for culling false positives from a raw pointset. These interpretations are based on evaluating event attributes such as: amplitude, SNR, arrival coherence, etc. Statistical methods for evaluating thousands to millions of candidate 'events' from a raw processing output pointset are necessary to cull obvious false positives resulting in a manageable subset of potential true positive events for further evaluation and final culling.

Source or focal mechanisms

The computation of source mechanisms for microseismic events is important for determining stress field characteristics as well as the sense of breakage or slippage in a pointset. In order to compute source mechanisms a well-sampled wavefield is necessary. The required sampling is available from multiple observation downhole systems and from wide-azimuth, high-fold, large aperture surface and near-surface systems.

Discrete fracture network and simulated reservoir volume computations

Deriving 'beyond the dots' estimates of hydrofracture discrete fracture network (DFN) and computing simulated reservoir volumes (SRVs) is of increasing interest as evaluation of the effectiveness of reservoir stimulation matures.

Uncertainty

We now come to uncertainty. From this review of both downhole and surface/near-surface recording geometries for use in passive seismic applications, it can see that the pros and cons of all the acquisition geometries informs fundamental interpretation issues including: determination of tensile vs shear failure modes; what is meant by the terminology 'microseismic fractures'; hypocentre positional uncertainty; pointset event count; pointset 'surprises' revealing previously unknown geological hazards; discrimination of 'false positive' from 'true positive' events.

If we now revisit uncertainty, in practice this arises in two primary contexts of this process. The first is in the detection step: how certain can we be that the detected events are, in fact, true microseismic events and not spurious noise? The second relates to the event localization: how accurate are the positional estimates, especially in the vertical direction?

Detection theory provides some insight into the first question (Johnson and Dudgeon, 1993). The basic test in detection theory is the choice between two hypotheses: H0 = signal absent, and H1 = signal present. The Neyman-Pearson lemma (1933) shows that it is possible to construct a likelihood ratio test to specify this choice which minimizes the chances for incorrectly choosing H1 when there is no signal present (a false-alarm). The likelihood ratio test can be equivalently specified by a sufficient statistic which is compared to some threshold value, where values of the statistic below the threshold indicate no signal present, and values above the threshold indicate the presence of signal. By specifying the test in this manner, one effectively fixes the probability of false-alarms in the system. In general, it is not possible to choose a statistic/threshold combination that reduces the probability of false-alarms to zero, so one must accept some probability of false-alarms. In practice, one must balance the false-alarm probability against the probability of failing to detect valid signal.

The SNR value we compute in the detection phase is such a sufficient statistic for a likelihood ratio test. The actual false-alarm probability in the system is determined by the distribution of noise after beamforming. If, for example, one is to assume the noise is Gaussian and the trailing window RMS measure is a valid estimate of the standard deviation of this distribution, then a SNR threshold value of 2 would result in a false-alarm probability of ~2.5% (the approximate cumulative probability of the Gaussian distribution above 2 standard deviations). Thus, for every 1000 windows examined where there is in fact no signal, we should expect 25 false-alarms with SNR greater than 2. If we restrict ourselves to windows with SNR greater than 3 (false-alarm probability of ~0.1%), we should expect to see only 1 false-alarm. Therefore, under the assumptions listed above, a SNR increase results in a decrease of the likelihood of a given trigger being a false-alarm.

While it is difficult to assign a certainty to an individual detected event, detection theory does supply some useful insights to the event catalogue as a whole. First, we know that the event catalogue will contain some percentage of false-alarms. Second, certainty in the event should increase with estimated SNR.

Estimating an event location ultimately comes down to selection of an optimal focusing or imaging point. Uncertainty in this estimate is driven by the effect of noise in this selection process. While the particulars of how noise interacts with the selection process are specific to the selection algorithm, we can predict that noise will tend to move the estimated location along contours of the migration point response and that the impact of noise should decrease with increasing SNR.

Synthetic modelling

In order to assess both types of uncertainty, we constructed a synthetic data set which was used in our imaging algorithm to locate events with varying amounts of noise.

The synthetic data set consisted of a surface array of 1000 channels arranged in a radial pattern of eight arms equally spaced in azimuth. Each arm consists of 125 channels spaced at 100 ft with an initial offset of 1000 ft from the centre of the array resulting in a maximum offset of 13,400 ft. One hundred events at a depth of 10,000 ft and located near the centre of the array were modelled using a 30 Hz centre frequency minimum-phase Ricker wavelet with a constant moveout velocity of 12,000 ft/s.

For a range of input SNR levels (0.02-20), Gaussian noise was added to the modelled data and imaged with the migration routine with the detection threshold set at 2. The event catalogue output by the migration was then compared to the known origin times and locations of the modelled events. A detected event with an origin time within 100 ms of a modelled event was considered a true detected event (a hit) while all other events are considered false-alarms.

Figure 1 shows the number of hits and false-alarms for each output SNR level. For SNR > 2, all 100 of the seeded events were detected. For SNR < 2, the detection rate rapidly drops, effectively reaching zero for SNR < 1. This behaviour suggests that we can use SNR as an indicator of reliability in the performance in the algorithm. Above some SNR threshold valid events are reliably detected, while below this threshold valid events are missed.

For all output SNR levels, the number of false-alarms remains approximately constant at a value of 10. While constancy is expected from detection theory, this value is much lower than one might expect for a 2.5% false-alarm rate. The 100 events were seeded at 2 second intervals into a 200 second long data set sampled at 4 ms. In the triggering routine, the event window moves forward sample by sample.

Thus, we examine 50,000 potential triggers and should expect 1250 false-alarms in the triggering phase. However,

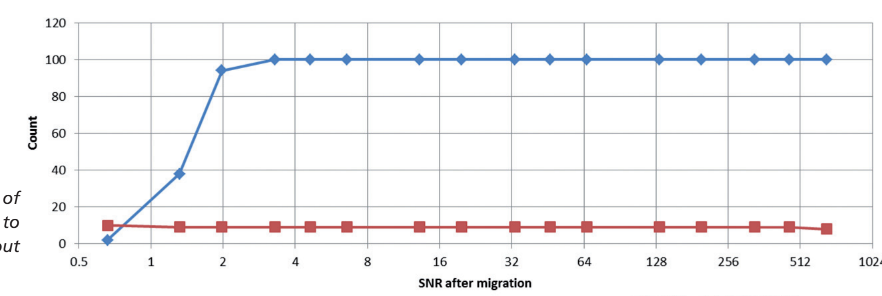

***Figure 1** Count of detected events as a function of SNR after migration. Detected events matched to modelled events are shown as hits, events without a match are shown as false alarms.*

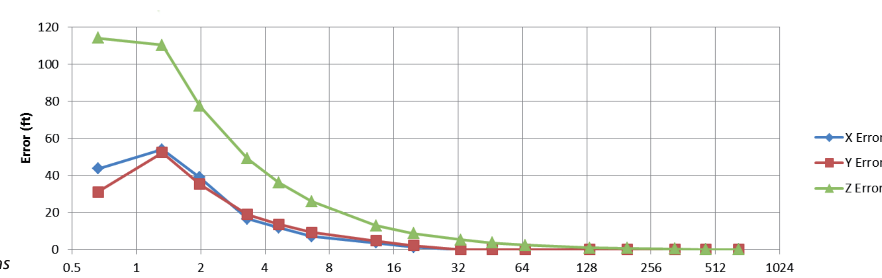

***Figure 2** Standard deviation of positional errors as a function of SNR after migration.*

www.firstbreak.org © 2013 EAGE

the 10 false-alarms shown in Figure 1 are those that were triggered but also passed the event localization step. Part of the event localization step is a requirement that the triggers show consistency over the time/depth trade-off trajectory. If the algorithm fails to find this consistency, the trigger is discarded. Thus we add further constraint against false-alarms.

Figure 2 shows the standard deviations of positional errors computed from the matched events (hits) shown above. Not shown in the figure are the average errors, for SNR >1 average errors are very close to zero for all three dimensions indicating the estimates are unbiased. For SNR >1, we see an exponential decline in variability of the errors, with horizontal and vertical uncertainties converging to near zero for very high SNR values. Variability in X and Y are approximately equal and 2–3 times smaller than variability in Z. The rate of decline in variability in all three dimensions is approximately the same. The estimates with SNR <1 should be discounted as it contains only two hits, and origin time errors associated with these two hits are significantly larger than the other hits (50 ms vs. 5 ms), indicating these are not likely valid matches.

As predicted, sensitivity to noise in the vertical direction is greater than in the lateral direction. The relative magnitude of the vertical and horizontal sensitivity is roughly proportional to the elongation of the migration point spread response. Furthermore, the impact of noise on the positional estimates diminishes rapidly with increasing SNR.

While SNR can be used to infer the relative likelihood that a given event is real, false-alarms will occur, discriminating the real event from the false will require additional information beyond SNR.

Synthetic modelling is useful in assessing the performance characteristic of the imaging method, but a number of simplifying assumptions were made that differ from actual application of the method. First, our model assumed that travel-times were known exactly. In practice, velocity and static corrections must be estimated from calibration shots (sources at known locations in the subsurface). While travel time errors are most likely to decrease the SNR after migration, long period errors in travel times could cause spurious focusing and add uncertainty.

Secondly, the model assumed the additive noise was Gaussian. While this is a reasonable first approximation, it does not take into account coherent noises, which are ubiquitous in surface and near-surface microseismic monitoring. Appropriate preprocessing can reduce the impact of coherent noise, but residual coherent noise will trigger false-alarms. Moreover, the number of false-alarms rejected in the event localization step will likely not be so high, as coherency in the noise will imply some additional consistency among triggers not seen in the model.

Uncertainty: the next step

As discussed earlier, to further define the uncertainty quantitatively we can utilize sophisticated tools in estimation theory, such as maximum likelihood estimators (MLEs) and the Fisher Information Matrix (FIM). MLEs help us to understand the behaviour or value variation of attributes, such as positions (x,y,z) with respect to each other. These value variations with respect to one another are called covariances. The systematic study of the many attribute pairings, and each pairing's variances, tell us important information about the stability or confidence that can be ascribed to the particular attribute under consideration. Further the FIM then tells us the 'information' content of the values we have evaluated with the MLE tool. If an attribute's particular value is relatively stable or invariant with respect to other attribute values (such as positions, i.e., x,y,z's), then we would say the information content is high, or that the value is fairly certain, or not uncertain.

On the other hand, if the information content of the value is poor, that value would tend to be variable, or not stable, with respect to other attribute values, i.e., certainty is low, or uncertainty is high. The MLE and FIM tools allow systematic evaluation of the stability of the attributes in question with respect to one another, and allow us to quantify that stability, or uncertainty.

In addition, these tools can be applied to *all* attributes. A microseismic event has many, many attributes, starting from position in space and time – x,y,z,t – to SNR, to processing attributes such as coherency, semblance, amplitude, magnitude, etc.

Understanding the context and tools above allow for an unprecedented level of quantified uncertainty analysis for important attributes, such as position in space and time, x,y,z,t.

Acknowledgement

This paper is a summary of various published and unpublished work by Michael Thornton and Mike Mueller of MicroSeismic, Inc, Houston, USA and Leo Eisner of the Institute of Rock Structure and Mechanics, Czech Republic. Their contributions are gratefully acknowledged.

References

Duncan, P. and Eisner, L. [2010] Reservoir characterization using surface microseismic monitoring. *Geophysics*, **75**, 5, 75A139–75A146.

Sarkar, S., Jupe, A., Shemeta, J., Langan, and Rosca, [2012] Uncertainty in microseismic event source locations associated with a fracture stimulation in a tight sand. *International Geophysical Conference and Oil & Gas Exhibition*, Istanbul, 1–4.

Thornton, M. and Eisner, L. [2011] Uncertainty in surface microseismic monitoring. *81st SEG Annual Meeting*, Expanded Abstracts, 1524–1528.

Warpinski, N. R., Du, J. and Zimmer, U. [2012] Measurements of hydraulic-fracture-induced seismicity in gas shales. *SPE 15159*

© 2013 EAGE