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Case study

Neuro-evolutionary event detection technique for downhole microseismic surveys

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ABSTRACT

Recent years have seen a significant increase in borehole microseismic data acquisition programs associated with unconventional reservoir developments such as hydraulic fracturing programs for shale oil and gas. The data so acquired is used for hydraulic fracture monitoring and diagnostics and therefore, the quality of the data in terms of resolution and accuracy has a significant impact on its value to the industry. Borehole microseismic data acquired in such environments typically suffer from propagation effects due to the presence of thin interbedded shale layers as well as noise and interference effects. Moreover, acquisition geometry has significant impact on detectability across portions of the sensor array. Our work focuses on developing robust first arrival detection and pick selection workflow for both P and S waves specifically designed for such environments. We introduce a novel workflow for refinement of picks with immunity towards significant noise artifacts and applicability over data with very low signal-to-noise ratio provided some accurate picks have already been made. This workflow utilizes multi-step hybrid detection and classification routine which makes use of a neural network based autopicker for initial picking and an evolutionary algorithm for pick refinement. We highlight the results from an actual field case study including multiple examples demonstrating immunity towards noise and compare the effectiveness of the workflow with two contemporary autopicking routines without the application of the shared detection/refinement procedure. Finally, we use a windowed waveform cross-correlation based uncertainty estimation method for potential quality control purposes. While the workflow was developed to work with the neural network based autopicker, it can be used with any other traditional autopicker and provides significant improvements in pick detection across seismic gathers.

1. Introduction

Microseismic monitoring has become an integral part of most unconventional resource development programs. They have found wide utility in reservoir monitoring as well as resource characterization studies. Phase arrival information is critical in identifying other microseismic source parameters of relevance such as event size and hypocentral location. One of the most common algorithms for detection is the short term averaging/long term averaging (sta/lta) algorithm (Allen, 1978). Methods based on abrupt changes in attributes of the seismic waveform such as higher order statistics (skewness and kurtosis by Saragiotis et al. (2002)) have also been used. Modern autopickers can use advanced techniques such as cross-correlation analysis (Song et al., 2010), polarization obtained from signal covariance matrix (Fischer et al., 2007), parallelized filters (Lomax et al., 2012), Bayesian probabilistic approach for concurrent events (Wu et al., 2015), singular value decomposition of 3-C seismograms (Kurzon et al., 2014) and robust statistical techniques (Chen, 2005). Noise artifacts can cause autopicker efficacy to gradually degrade though the effect of different types of noise on different autopickers can vary significantly. For downhole sensor deployments, the quality of the first arrival pick is related to sub-surface structure (such as velocity contrasts and layering), source type, source–receiver geometry, and finally, downhole noise conditions. These factors can lead to complicated wave-trains (such as head waves and reflections) and require human intervention to prevent miss-picks. Finding a robust methodology to work under extreme noise conditions is therefore a significant challenge.

In this article we use a robust hybrid neural network autopicker (Maity et al., 2014) to make initial pick estimates. Then we use an evolutionary algorithm to make the best possible arrival detection based on the initial pick estimates. The basic assumption behind the suggested approach is that moveout behavior of direct arrivals

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is predictable as it is hyperbolic and can be approximated using a high order polynomial function. The algorithm has been extensively tested on real microseismic monitoring data from multiple gas well completions in the Marcellus shale reservoir and the results have been compared with contemporary autopickers in use by the industry to validate, both qualitatively and quantitatively, the applicability of our proposed approach. The use of genetic algorithms allows for optimized search and rapid detectability even for extremely large gathers (hundreds of data channels).

2. Method

2.1. Neural network based autopicking algorithm

A robust neural network based autopicking approach is used to make initial pick estimates. Maity et al. (2014) provide a detailed understanding of the autopicking workflow used for this study and can be used as a reference. In brief, the workflow involves preprocessing steps such as noise removal through application of frequency filters, data rotation to maximize phase arrival energy on corresponding components, etc. For selection of training, validation and testing data subsets, a careful selection procedure is used to account for various arrival artifacts ranging over significant spread of the energy and frequency spectrums of the dataset being processed. For network input design, multiple seismic data attributes are evaluated (such as wavelet transform, statistical measures, or others from available autopicker algorithms, etc.). Data subset selection involves careful analysis of the filtered spectrum and identifying phase types of interest and making sure that the corresponding phase arrivals are picked up with reasonable accuracy by some, if not all of the selected data attributes. At the same time, various incoherent noise artifacts are also selected within the data subsets for improved training of network models as classifiers. In short, representative training dataset should include interference, reflection, refraction and other propagation and noise effects that are typically observed in downhole microseismic survey datasets being studied. Next, any redundant attributes are identified and pruned by correlation of normalized and rescaled attribute measures. The aim is to minimize the number of attributes to be used in the training process to reduce run times and to increase the accuracy without dilution in results due to too many attributes or by having a non-representative model due to too few attributes. A neural network is used to map the input attributes to an output characteristic function which has highs of 1's at the phase onsets and 0's otherwise. The data subset selected is subdivided into training, validation and testing sets using statistical measures such as mean and skewness of distribution to verify representativeness. The nodal inputs to the network are defined by the selected attributes. The hidden layer is designed based on the number of input and output layer nodes. An evolutionary algorithm is used for network optimization. The output characteristic function as obtained by applying the trained network on any dataset is used for pick selection as required and we will call this function as AP1 for future reference.

2.2. Contemporary picking algorithms

Two contemporary autopicking algorithms were tested in a comparative framework along with the proposed hybrid AP2 workflow in order to test and benchmark its performance. The first method used is the FilterPicker algorithm which involves multiple filters operating in parallel. The final picker characteristic function is calculated as the envelope from a derived function which combines the results from each filter. Lomax et al. (2012) provide a very detailed understanding of the FilterPicker workflow. The other picking algorithm used is the standard “sta/lta” averaging method as implemented within microseismic monitoring (MIMO) package developed by NORSAR. The signal detections or first break picks are made based on signal-to-noise ratio crossing predefined threshold and falling back below threshold within a reasonable time interval. Oye and Roth (2003) provide a detailed understanding of the picking and phase detection algorithm used within MIMO package. In this study, errors generated by the processing packages were disregarded and actual time offsets based on comparisons with manual picks were used for evaluation.

2.3. Pick refinement

Based on the output map obtained from any of the mentioned picking workflow, we expect higher values of characteristic function to be indicative of possible pick locations and vice versa. The picking approach involves time averaging of the autopicker characteristic function before using limiting thresholds predefined by the user. As the average moves beyond the defined threshold, a possible pick is declared and then a check is made to ensure that the time averaged value of the characteristic function falls below the defined threshold before a second pick can be considered. Once a pick is declared, the algorithm selects the peak (local maxima) on the picker characteristic function as potential pick location within the defined pick window (as obtained based on when the value of the time averaged characteristic function rises above and falls below predefined thresholds). A quality control mechanism can be used which checks for ratio of two statistical measures (mean and maximum) across the pick within the identified pick window and picks are quality controlled based on these ratios.

2.4. Evolutionary search for optimal pick across gathers

Before final detection using evolutionary search, misclassified picks can be removed if necessary using a weighted pick density criteria which is evaluated for each pick. This criteria and its use is based on the fact that for borehole geophone strings, the moveout is generally smooth across the gather for seismic events. This indicates that if a pick is located accurately on an individual trace across a seismic gather, it should be straddled with other picks as we move along the gather due to proximity of geophones compared with typical travel paths. The density measure is computed for ith trace by using a weighted summation approach along each pick within a predefined evaluation window as shown in Eq. (1).

$$\tau_P(i)=\sum_{j=i-N_t}^{i+N_t}\sum_{k=\tau(j)-win}^{\tau(j)+win} AP1_{j,k} \tag{1}$$

Here, N_t defines the number of traces close to the evaluation trace for calculation which can even include all traces across gather when looking for far-field events. The variable k allows for summation over a predefined window size where presence of other picks increases pick density. This measure is normalized based on the observed maximum and minimum over all picks made using AP1 characteristic function. Finally, the picks associated with the lower nth percentile of the density distribution are pruned as erroneous provided the evaluated signal-to-noise ratio taken cumulatively for all traces is reasonably low. Fig. 1 shows a sample gather with the initial picks and the final pruned picks using this measure. For this study, we use a cutoff at 10th quantile, i.e., any pick location with a probability falling below the 10th quantile of associated probability function is removed.

With the picks from the refinement step available for analysis, evolutionary search can be applied to detect events across gather. As indicated earlier, this technique is only applicable for borehole