geoconvention
Calgary • Canada • June 17-19 2024

Computer Vision Approach for Automated Fracture Hit Detection in Low-frequency Distributed Acoustic Sensing

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Summary

Distributed Acoustic Sensing (DAS) is widely used for monitoring hydraulic fracturing operations. Low-frequency DAS (LFDAS) can depict information about far-field strain perturbations, as well as fracture opening. The identification and analysis of fracture hits (frac hits) in LFDAS are usually time-consuming and inefficient. We introduced a key feature Computer Vision workflow to automate the detection of frac hits and subtract the strain signal from the data. Reliability and computing performance are tested against 1D and 2D implementations of the Short-Time Average over Long-Time Average detector (STA/LTA). The computer vision workflow improves the location of frac hits in adverse scenarios, such as different locations in depth and short time spacing. The workflow is tested on real LFDAS data from western Canada, and the results show the opportunity to introduce a novel tool in hydraulic fracturing and geomechanics analysis.

Introduction

Hydraulic fracturing operations can be monitored using Distributed Acoustic Sensing (DAS). The hypersensitivity of fiber-optic sensing to temperature, strain and microseismicity makes it an appropriate tool for constraining and interpreting fracture hits (frac hits) during injecting stages (Karrenbach et al., 2017). At very-low frequencies (< 0.05 Hz), cumulative strain can be utilized to constrain fracture geometry and provide valuable information on the far-field effects of hydraulic fracturing operations. DAS optic-fiber serves as the sensor itself, leading to dense spatial sampling that makes it ideal for processing and imaging algorithms (Karrenbach et al., 2019).

A computer vision workflow was implemented to automate the detection of frac hits in LFDAS. The Oriented FAST and rotated BRIEF object recognition algorithm (Rublee et al., 2011) was adapted to locate and match features of interest (keypoints) between a template and different examples. Furthermore, the strain signals of frac hits are subtracted to assist the algorithm in detecting several frac hits on the same stage while enabling an understanding of their underlying strain response. This is achieved using affine image transformations and warping (Nustes Andrade and van der Baan, 2021).

Theory and Method

The Computer Vision workflow identifies local keypoints that represent the most relevant features of an element of interest. The process then involves a *feature description* algorithm that simplifies the information of the keypoints into vectors. Finally, feature matching compares key points from the template with those in a test image based on a threshold of similarity. These features should be distinctive enough to locate objects in different scenarios of position, rotation, and temporal scale (Lowe, 1999). The Oriented FAST and rotated BRIEF (ORB) algorithm (Rublee et al., 2011) is used to perform the automatic detection of frac hits in LFDAS data points.

Oriented FAST and rotated BRIEF (ORB)

ORB uses the feature detection FAST (Feature from Accelerated Segment Test) to perform detection over each candidate pixel. Such analysis depends on a threshold and is invariant to affine transformations (rotation, translation, and reflection), ensuring real-world features can be detected from multiple views (Rosten and Drummond, 2006). With the intention of refining the detection, ORB classifies the selected keypoints using the Harris corner-ness measure, as well as iteratively convolving the original image with a Gaussian filter, followed by a down sampling operation (Nustes Andrade and van der Baan, 2021). ORB builds descriptors by comparing pairwise pixels through Binary Robust Independent Elementary Features (BRIEF) (Calonder et al., 2010). Finally, ORB compares pixels from two images using the Hamming distance, which measures the distance between two vectors that are the decomposed key features (Calonder et al., 2010, Nustes Andrade and van der Baan, 2021).

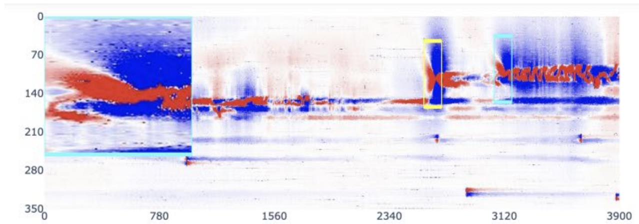
Affine image transformations and warping

After identifying frac hits, irrespective of their differences in size, position, and orientation using a universal frac hit template, extracting the strain signal requires precise knowledge of the template-induced shape changes. Affine transformations between the template and the located event facilitate this process. Affine transformations are a special kind of geometric transformation that preserves collinearity (lines) and distance ratios (midpoint distances are respected). The Random Sample Consensus (RANSAC) algorithm is employed for the estimation process (Fischler and Bolles, 1981). This algorithm randomly selects matching pairs from the images, and warping is applied to inversely map them on the LFDAS data. This way, matching points are detected, and the template's influence can be subtracted from the strain signal (Nustes Andrade and van der Baan, 2021).

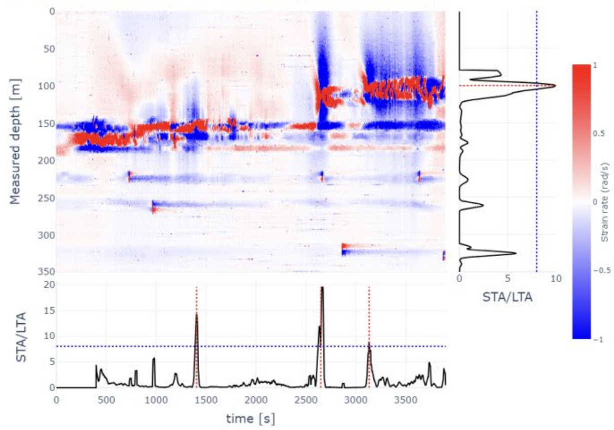
Results

We use LFDAS data from Western Canada to test the Computer Vision algorithm. In total, 10 stages were analyzed and compared against the 1D and 2D STA/LTA detector. Both frac hits of the test stage displayed in Figure 1a were detected by the computer vision implementation (2633 s and 104 m, 3110 s and 95 m, respectively, for the first and second frac hit).

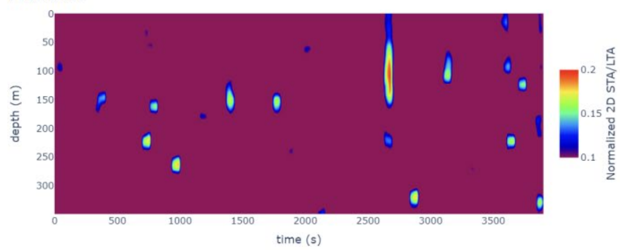
The results were compared with the 1D STA/LTA (Figure 1b). The results show that in time, there are three detections, of which one is a false detection. Fracture closing signals and rapid extensional-compressional signals influence the result by adding peaks of higher amplitude than the threshold. Meanwhile, in depth, only one event is being detected. The large amplitude peak in depth is mostly caused by the short time and depth spacing and depth between fracture openings, the effects of the crack tip must be considered as well. Figure 1c shows the normalized amplitude map of the 2D STA/LTA detections. Due to the nature of the implementation, frac hits with little spacing in time and depth could be wrongly detected as a single event. Moreover, strain tails can create false detections around the map, making filtering and analysis of the results more challenging.



(a) Computer vision detections, yellow first frac hit, and cyan second frac hit. At top right, a zoom of the second frac hit.



(b) 1D STA/LTA detection. The horizontal blue lines show the threshold of the detector, while the red vertical lines correspond to the detections.



(c) 2D STA/LTA normalized detection. Strong red colors correspond to detections.

Figure 1. Frac Hits detections by the Computer Vision algorithm (a). 1D STA/LTA detections over the same stage (b). 2D STA/LTA normalized map detection (c).

Discussion

The efficacy of the computer vision algorithm can be observed from various perspectives. Firstly, even though the template used for the detection belongs to a different stage, the algorithm employs a generalized search for frac hits, making it flexible for analyzing datasets. Additionally, its flexibility in detection extends beyond differences between stages to include variations in angles and orientation. Lastly, the algorithm compensates for the difference in size between the template (120×120 pixels) and the stages, which can be up to 350 × 7000 pixels, thereby optimizing computational usage for the detector.

Conclusions

The present study introduces a novel implementation of image processing suitable for the densely populated data points of LFDAS. The key feature detector ORB extends the detection of frac hits by subtracting the strain signal directly from the data using affine image transformation and warping. The described workflow represents an ideal tool for a reliable method for the automation of frac hit detection, complementing the interpretation of hydraulic fracture physics and adjustment of completion parameters. The method achieves better depth location of multiple frac hits compared to the classic STA/LTA method, as well as its 2D counterpart.

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