Real-Time Hydraulic Fracturing Analysis using Deep Learning Methodology

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- Part 2: Ball Pumpdown/Seat Event Recognition
- Part 3: In-Stage Slurry Rate Segmentation
- Use Cases
Hydraulic Fracturing 101

Sources: Internet
Real-Time Streaming Architecture

Analytics Models deployed here

Source: Cao, Loesel, Paranji, 2018, SPE-189595-MS
Stage Start/End Recognition
Ball Pumpdown and Seat

Plugs with balls
Part 1: Stage Start/End Recognition
Hydraulic Fracturing Stages

- Start: the fracture fluid start being injected into the wellbore.
- End: the pump is shut down and the fracture fluid is stop being injected into the wellbore.

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
The rule we are using is the following: for every time stamp, if the current slurry rate is greater than 0 bpm, the current well head pressure is greater than 300 psi and the previous slurry rate is equal to 0 bpm, this time stamp is labelled as the start of a stage. For every time stamp, if the current slurry rate is equal to 0 bpm, the current well head pressure is greater than 0 psi and the previous slurry rate is greater than 0 bpm, this time stamp is labelled as the start of a stage.
Moving Median Filter

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Methodology

- Human does not isolate each data point to determine its property.

- Human look at the previous and subsequent data, continuous streams of data to determine the properties of each time stamp.

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Deep Learning Model: Data Preparation

- Label time stamps as 0s and 1s: inside or outside a stage;
- Slice the time series data using a sliding window;
- Extend the features;
- Label the sample.

REFERENCE

Sources: xxx
Deep Learning Model: The Model

- Convolutional layer: extract high-level features
- Max pool layer: prevent overfitting
- Dense layer: classification

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Deep Learning Model: Metric

Time-stamp-wise accuracy:

$$acc = \frac{\text{Number of time stamps with correct label}}{\text{Number of total time stamps}}$$

Flag-wise accuracy:

$$acc = \frac{\text{Number of correct predicted flags}}{\text{Number of total flags}}$$

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
### Rule-Based Model

<table>
<thead>
<tr>
<th></th>
<th>Predicted Yes</th>
<th>Predicted No</th>
<th>Total Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Yes</td>
<td>TP = 648</td>
<td>FN = 0</td>
<td>648</td>
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<tr>
<td>Actual No</td>
<td>FP = 274</td>
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<td>4,911,944</td>
<td>4,912,866</td>
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</table>

### Deep Learning Model

<table>
<thead>
<tr>
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<th>Total Samples</th>
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<td>Total Prediction</td>
<td>730</td>
<td>4,912,136</td>
<td>4,912,866</td>
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</table>
## Analysis and Results

### Rule-Based Model

<table>
<thead>
<tr>
<th>Actual Yes</th>
<th>Predicted Yes</th>
<th>Predicted No</th>
<th>Total Samples</th>
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<tbody>
<tr>
<td></td>
<td>TP = 648</td>
<td>FN = 0</td>
<td>648</td>
</tr>
<tr>
<td>Actual No</td>
<td>FP = 105</td>
<td>TN = 4,912,113</td>
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<td>Total Prediction</td>
<td>753</td>
<td>4,912,113</td>
<td>4,912,866</td>
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</table>

### Deep Learning Model

<table>
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<th>Actual Yes</th>
<th>Predicted Yes</th>
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</thead>
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<td>FN = 9</td>
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<tr>
<td>Total Prediction</td>
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<td>4,912,866</td>
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</table>
Analysis and Results

<table>
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<tr>
<th>Tolerance</th>
<th>25 seconds</th>
<th>20 seconds</th>
<th>15 seconds</th>
<th>10 seconds</th>
<th>5 seconds</th>
<th>3 seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flag-wise accuracy</td>
<td>99.7%</td>
<td>99.3%</td>
<td>99.0%</td>
<td>98.5%</td>
<td>92.3%</td>
<td>68.1%</td>
</tr>
<tr>
<td>Accurate flags</td>
<td>646</td>
<td>644</td>
<td>642</td>
<td>639</td>
<td>598</td>
<td>441</td>
</tr>
<tr>
<td>Total flags</td>
<td>648</td>
<td>648</td>
<td>648</td>
<td>648</td>
<td>648</td>
<td>648</td>
</tr>
</tbody>
</table>

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Part 2: Ball Pumpdown/Seat Event Recognition
Ball Pumpdown and Seat

Plugs with balls
First Step: Deep Learning

- The ball pumpdown/seat event recognition is a two-step strategy.
- The first step is to tell if there is a ball pumpdown/seat event in a stage using image segmentation technique.
- The second step is to locate the end of the ball pumpdown/seat event if there is one.
- The second step can be achieved by a rule-based selection given the information from the image segmentation.

REFERENCE
First Step: Deep Learning

- Two-step Strategy
  - Tell if there is a ballseat
  - Locate the ballseat

- ‘Z’ pattern in the slurry rate

REFERENCE

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Data Preparation

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Model: Pre-trained ResNet + UNet

Sources: xxxx
For each column from a mask, if the fraction of pixels that are marked as positive exceeds a certain threshold, the corresponding time stamp is considered positive.

If there is positive area in the sample after processing by the rule, we say there is a ballseat event in this sample.

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN) counts are shown.

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted Yes</th>
<th>Predicted No</th>
<th>Total Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Yes</td>
<td>TP = 79</td>
<td>FN = 2</td>
<td>81</td>
</tr>
<tr>
<td>Actual No</td>
<td>FP = 8</td>
<td>TN = 90</td>
<td>98</td>
</tr>
<tr>
<td>Total Prediction</td>
<td>87</td>
<td>92</td>
<td>179</td>
</tr>
</tbody>
</table>

F1 score: 0.94
A Second Opinion

- Include the wellhead pressure into the training samples
- Use the same mask as the previous model

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Second Step: Rule-Based

Starting from the midpoint of the positive area (yellow):
- The first derivative of the wellhead pressure at the current time stamp is greater than 20 psi/s.
- The first derivative of the wellhead pressure at the subsequent time stamp is greater than 15 psi/s.
- The first derivative of the wellhead pressure at the second subsequent time stamp is greater than 10 psi/s.
- The first derivative of the slurry rate at the current time stamp is smaller than 0.01 bpm/s.

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Results

Confusion matrix with one model

<table>
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<td>92</td>
<td>179</td>
</tr>
</tbody>
</table>

Confusion matrix with two models voting

<table>
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<tr>
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<th>Predicted Yes</th>
<th>Predicted No</th>
<th>Total Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Yes</td>
<td>TP = 78</td>
<td>FN = 3</td>
<td>81</td>
</tr>
<tr>
<td>Actual No</td>
<td>FP = 3</td>
<td>TN = 95</td>
<td>98</td>
</tr>
<tr>
<td>Total Prediction</td>
<td>81</td>
<td>98</td>
<td>179</td>
</tr>
</tbody>
</table>

F1 score improves from 0.94 to 0.97

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Part 3: In-Stage Slurry Rate Segmentation
In-Stage Slurry Rate Segmentation

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
In-Stage Slurry Rate Segmentation

1. Median Filter
2. Butterworth Low Pass Filter
3. Recursive Median Filter

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
• Adjacent segments with the same classification are joined into one larger segment.

• If a constant rate segment is surrounded on both sides by ramp-up segments, then perhaps it should be converted to a ramp-up segment as well.

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Use Case
Use Case

Sources: Shen, Y., Cao, D., Ruddy, K. 2020. SPE-199738-MS
Backup slides