RAPID RIG AUTOMATION Performance Improvement in Drilling

April 26, 2017
SPE DSATS Webinar

From Data to Actions -
Improving the Value of Drilling Data in Operations, Engineering, and Research

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April 26, 2017

THE UNIVERSITY OF TEXAS AT AUSTIN

Agenda

- Introduction
- Data Interpretation
- Data Requirements
- Data Application Examples
- Data Structures and Metadata

Data Projects @ UT Austin

Real time operating center
- Data (real time or memory) from different operators and service providers
- Software from 10+ providers
- MATLAB, R, Spotfire, Excel

Data projects
- Downhole data
- Wellbore positioning/tortuosity
- Directional drilling automation
- Performance evaluation
- Data structures and standards

Involvement
- Eric van Oort, Pradeep Ashok (supervisors)
- 4 PhD students, 10+ undergrad students per semester
- Support from industry

More information: drilling.utexas.edu, SPE Webinar: Drilling Optimization, Risk and Uncertainty Reduction, and Future Workforce Education Using Big Data Analysis by E. van Oort, Feb 2017

From Automation to Optimization

"Taking the Art out of Drilling"

Data / Measurements

Procedures | Algorithms | Control

Long Term Goal — Leads to — Short Term Success

Drilling Automation

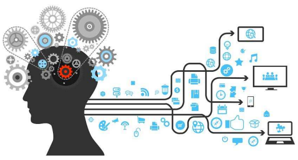
- Autonomous Rig
- Optimized Drilling through DH Controls
- Drilling Advisory System

Drilling Optimization

- Gains in Information / Knowledge
- Standardization of Processes
- Reduction of Operational Variability and Risks

The Promise of Artificial Intelligence

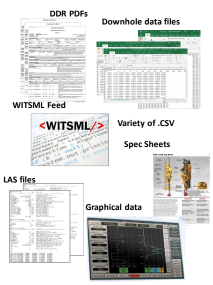
- Artificial intelligence, big data, machine learning, data mining, etc. as a universal problem solver
- Sentiment: "Data problems will be overcome automatically"
- AI holds incredible opportunities
- 90% of big data analysis is data curation
- *There will be no magic!*
- Hard work and effort to prepare our data for such applications



"It's gonna be great!"
– D. J. Trump

We have a Messy Data Problem

- "We don't have a big data problem, we have a messy data problem"
- Contextual information essential but not digitized - DDR:
  - 'problmes /w toppdrive' ← typos
  - Wait on weather
- Can be digitized – to showcase successful applications
- "Big data" applications – data needs to be
  - comprehensive
  - complete
  - comparable
  - categorized



A Basic Example of Data Mining

Indirect diagnosis of Diabetes from patient data:

10,000s of patients → > 100 Features

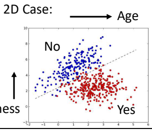
	BMI	Blood Pressure		Smoke	Waist	RI	Diagnosis
Patient 1	22.5	134.4	72.9	1	3.2	1	**Yes**
Patient 2	16.6	96.7	59.1	0	4.1	1	**No**
~~**Patient 3**~~	~~29.1~~	~~127.5~~	~~NaN~~	~~0~~	~~2.3~~	~~1~~	~~**No**~~
Patient 4	20.6	136.4	80.4	3	2.4	0	**No**
Patient 5	27.5	134.1	83.2	4	3.9	1	**Yes**
Patient 6	18.3	128.2	83.1	0	3.1	0	**No**
~~**Patient 7**~~	~~30.2~~	~~110.2~~	~~NaN~~	~~1~~	~~NaN~~	~~0~~	~~**No**~~
		109.2	63.8				**No**

Use unique identifier | **Continuous Variables** | **Classes** | **Binary Variables** | **Prediction Goal**

Every feature is standardized and classified! E.g. BMI

Source: Kaggle AI challenge, www.kaggle.com

- Classification using supervised learning
- Split in test and train set
- Use algorithms
  - Logistic regression, Neural network, Bayes classifier, …
- Use test data to evaluate results
- Model applied to new data
- 2D Case:



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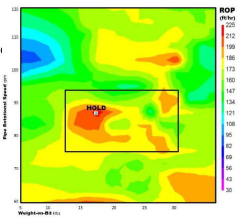
Barriers to Applications in Drilling

- ***Time series data***
  - Lots of volume, but single data point not telling
- ***Impact factors*** are not categorized and standardize
  - What impact has the placement of the stabilizer, how to categorize position?
- Not all impact factors are captured into ***features***
  - Human impact
  - No sensors available
- ***Scarcity of data***
  - Heat Map: Enough data means rich data set for all combinations of RPM vs WOB and ROP per
    - Formation, BHA design, Bit, Rig, etc.
  - Physics models or other smart algorithms may help to reduce data requirements
- ***Lack of comparability*** between wells



Heatmap of RPM vs. WOB, finding the ROP sweet spot. Is our data big enough?

Source: NOV Drillshark: http://www.epmag.com/highway-downhole-data-delivers-optimized-drilling-1461126, Feb 2017

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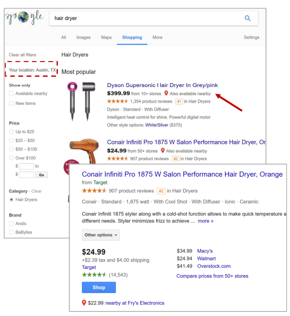
Example from AI leaders: Google Shopping

- Google shopping:
  - Search for stores and prices in current location
- Real time updates require stringent specifications and categorization
- Google's algorithms don't work perfectly either
- Manual input required:
  - Data centers with thousands of employees in India that also manually sort through data
- Effort required for results



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It's all about baby steps

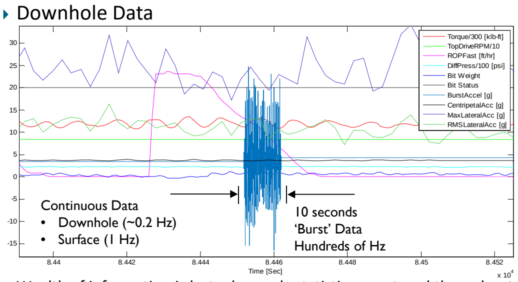
- **Continuous improvement process**
  - Show potential of data with stand alone applications
  - Define data structures to solve specific problem
  - Specify data requirements
  - Implement structures
  - Open options for new applications
  - Define additional structures
  - Etc.
- **Solving current problems**
  - Data interpretation
  - Data sample rate requirements (for detecting dysfunctions)
  - Data format framework
  - Simple but robust data correction algorithms

Polling Question

- Who should own drilling data (valuable for the drilling process)?

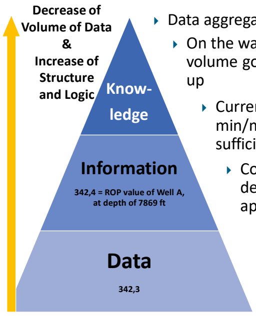
Data Aggregation – Downhole Data

- Downhole Data



- Wealth of information is lost when only statistics are stored throughout the entire run

Data, Information, Knowledge



- Data aggregation
  - On the way up, the density of information/data volume goes down, structure, logic, and costs go up
    - Current approach is rudimentary (e.g. min/max/avg), which may or may not be sufficient
      - Correct data aggregation method depends on the requirements for each application
        - Currently, essential information is lost when applying standard aggregation methods.

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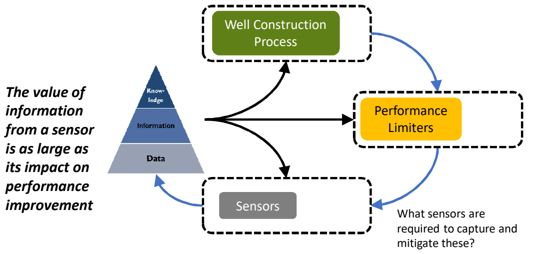
Value of Information

- Well construction process is not perfect due to a variety of drilling performance limiters.
  - E.g. Wellbore misplacement, reduced ROP, unnecessary loads on tools, etc.



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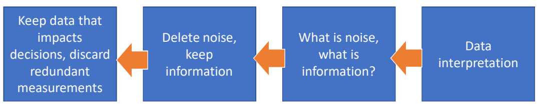
Data Aggregation

- Easy in theory, difficult in practice
- Aggregation
  - Data reduction of time series data
  - Elimination of redundant data
  - Merging of different data types (static, time based, depth based, contextual, etc.)



- Data aggregation depends on the application
- Sensor design plays a key role in aggregation research

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Data Interpretation

Automation Requires Downhole Data

"In other industries, you either know the physics or you have enough experimental data. We have neither."

Quote from 'From Sensors To Solutions' Workshop

- Downhole data enables
  - Accurate ***information*** on complex downhole environment
  - Post well analysis driving ***learnings*** for new wells
  - Better ***prediction*** of downhole parameters based on surface data
  - Essential for ***automated drilling operations***, but need to establish trust in the data
- Downhole data
  - Difficult to access (downhole to surface transfer)
  - Difficult to interpret (no 'outside' observer)

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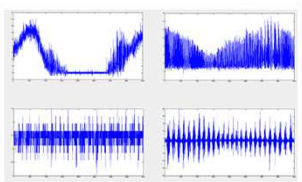
Data Interpretation

- Petrophysics
  - Understand the physics of the tool, measurement and the operational circumstances
  - Understand data processing
- Dynamics data for drilling automation and performance improvement - awareness is not (yet) present
- Closing the gap between sensors and data interpretation to differentiate noise from information
- Inverse problem: How did the sensor move to create these patterns



High Frequency Burst Data - Accelerations 10 Sec

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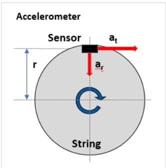
Interpretation of Tangential Accelerations

Inverse Problem: How did accelerometer move to produce the observations in the measurements?

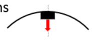


$a_r = \omega^2 r$

$a_t = \dot{\omega} r$

In Theory

- Radially placed accelerometer (centripetal) measures lateral vibrations



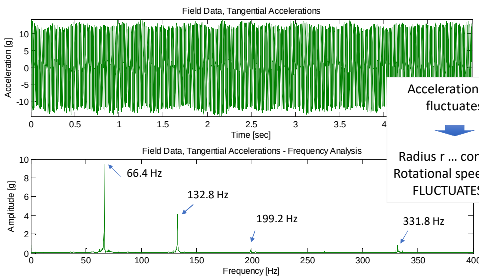
- Tangentially placed accelerometer measures torsional vibrations

Source: Macpherson et al., 2015

Source: Macpherson et al. 2015

High Frequency Torsional Oscillations?

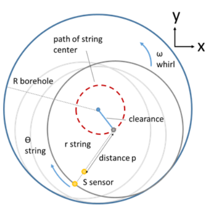
- Tangential accelerometer measures high frequency vibrations:



Acceleration a … fluctuates

Radius r … constant
Rotational speed ω … FLUCTUATES??

What if the string rotates off center?



Kinematic Model

using 2 Equations

For backward whirl:

$x_b(t) = +\delta\cos\omega t + r\cos\theta t$
$y_b(t) = +\delta\sin\omega t - r\sin\theta t$

For forward whirl:

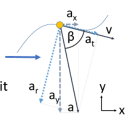
$x_f(t) = +\delta\cos\omega t + r\cos\theta t$
$y_f(t) = -\delta\sin\omega t - r\sin\theta t$

Convert to Sensor's Frame of Reference

Radial and tangential components using

A) geometry (numerical method)

B) Tensor Calculus (explicit formulation)



Source:

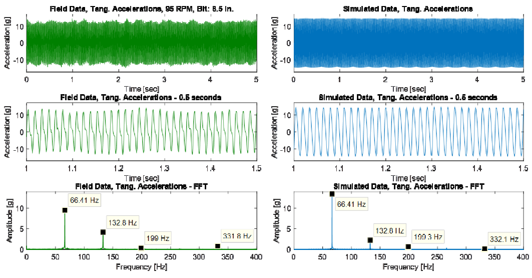
What if the string rotates off center?

Video1

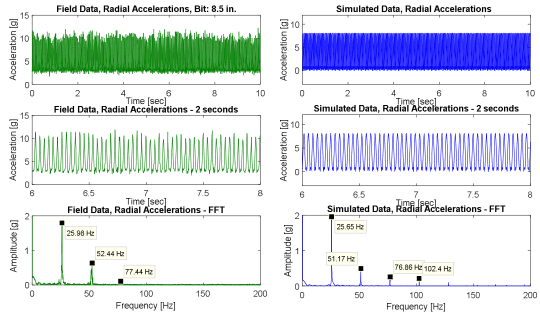
Radial and Tangential Acceleration Components

Video2

Tangential Accelerations: Field and Simulation



Radial Accelerations: Field and Simulation



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Conclusions: data interpretation

- ***Fictious forces*** due to coupled rotation:
  - These forces can be considered noise
  - Off-center rotation probably not harmful to the drillstring, stress amplitudes are low
- Off-center rotation:
  - Sensor does not represent the entire drillstring
  - Equations for uniform rotation do not apply anymore
- Data aggregation:
  - Capturing amplitude and frequency is enough

Disney's Mad Hatter Tea Party

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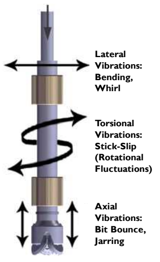
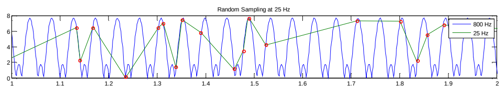
Defining Sampling Rate Requirements

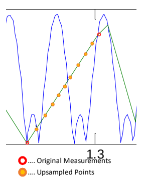
- Large data sets with high frequency downhole dynamics data
  - Accelerometers
  - Gyros, magnetometers
  - Strain gauges
  - Pressure, temperature
- Study of known dysfunctions
  - Vibrations
  - Hydraulic dysfunctions
  - Weight transfer
  - Etc.
- Define sampling rate requirements for detection of dysfunctions
- Separate signal from noise



Source: SPE 174986

Theory: Nyquist Sampling Rate





- Nyquist theorem states that the sample frequency needs to be at least twice as high as the highest frequency of interest.
- E.g. Whirl at 150 Hz needs 300 Hz or more
- Upsampling
  - = adding additional points in between two measurements
  - Higher frequency phenomena cannot be reconstructed
  - Interpolation between points

Nyquist Frequency Theorem

Recommended Sampling Rates I

Type	Sub-Category	Comments	Observed Typical Frequency/Periods	Data Sampling and Processing Rate
Lateral Vibrations				
	Backward Whirl	Additional dynamic component, high amplitudes, negative radial accelerations	Up to 120 Hz +	250 Hz +
	Forward Synchronous Whirl	Identified from bit wear, whirl speed equals rotational speed, low frequencies	< 3 Hz	10 Hz
	Off Center Rotation	Only movement of the sensor without dynamical forces, very high frequency spectra of overtones (500 Hz+)	First mode up to 70 Hz + overtones	250 Hz +
	Chaotic Whirl	Described in literature, not (yet) identified in data		
Torsional Vibrations				
	Harmonic Stick Slip	Period depends on length of drill string, negative rotation can occur	<0.1 – 2 Hz	5 Hz
	Torsional Fluctuations	Frequencies related to RPM, Different sources, e.g. stabilizers, doglegs, buckling,	0.5 Hz – 10 Hz	20 Hz
	Lithology changes	Correlation with tangential acceleration, depth based	< 1 Hz	< 2 Hz
Axial Vibrations				
	Bit Bounce	Harmonic axial fluctuation of high amplitude	5-20 of Hz	50 Hz
	Vibrational Dynamics	Effects of lateral and torsional vibrations on axial vibration measurements	Up to 120 Hz	250 Hz +
	RPM Fluctuations	Stress and strain changes for each rotation, especially in curve section	0.5 Hz – 10 Hz	30 Hz

Source: SPE 174986

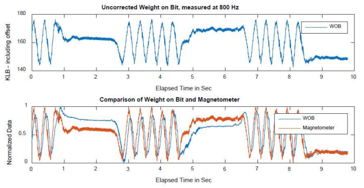
Recommended Sampling Rates II

Downhole Weight on Bit				
	Weight transfer	Low frequencies	< 1 Hz	< 2 Hz
	Dynamics (Vibrations)	Whirl and stick slip frequencies	Up to 120 Hz	250 Hz +
	Bit Bounce	Harmonic fluctuation, medium frequency	5-20 of Hz	50 Hz
Downhole Torque				
	Torque Transfer	Due to friction, buckling	0.5 Hz – 10 Hz	20 Hz
	Torque Fluctuations	RPM related	0.5 Hz – 10 Hz	20 Hz
	Dynamics (Vibrations)	Whirl and stick slip frequencies	Up to 120 Hz	250 Hz +
Pressure				
	Kick detection	Pressure increase due to influx	< 1 Hz*	< 2 Hz
	ECD monitoring	Cuttings transport, surge and swap	< 1 Hz*	< 2 Hz
	Changes in DH pressure regime	Depending on DH pressures, ECD, pump rates, etc.	< 1 Hz*	< 2 Hz
	Dynamics (Vibrations)	Pressure fluctuations based on pipe movements	Up to 120 Hz	250 Hz +
Temperature				
	Temperatures	Low frequencies	< 1 Hz	< 2 Hz

Source: SPE 174986

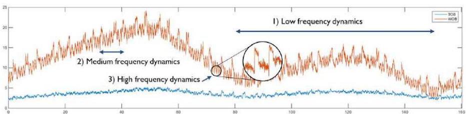
Downhole sensors capture all dynamics

- Regardless of the 'direction' of the measurements, downhole sensors capture all dynamics:
  - Lateral accelerometers measure axial dynamics
  - Axial accelerometers measure lateral dynamics
  - Strain gauges measure all movements



Differentiation by Frequencies

- *Low frequency dynamics*
  - Trends and graduate changes
  - Examples: Surface parameter adjustments, changes with low or *no periodicity*
- *Medium frequency dynamics*
  - Periods of several seconds
  - *Examples: Rotational movements, stick slip vibrations*
- *High frequency dynamics*
  - Frequency > 1 Hz
  - Whirl currently known highest high frequency downhole phenomenon

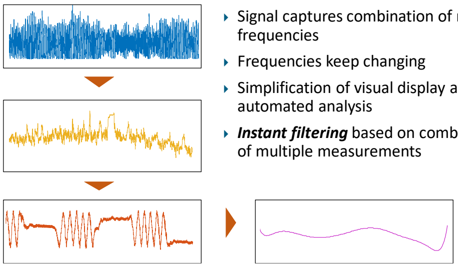


- *Sensors capture all dynamics regardless of the sensor's purpose*

Source: SPE 174986

Selective Filtering to Remove Noise

- Signal captures combination of multiple frequencies
- Frequencies keep changing
- Simplification of visual display and automated analysis
- ***Instant filtering*** based on combination of multiple measurements



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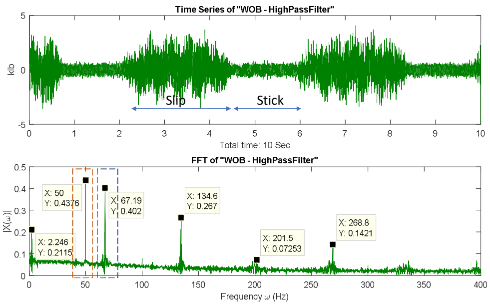
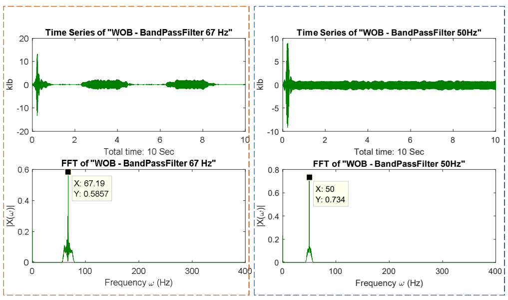
Source: SPE 174986

Weight on Bit Under Stick Slip Vibrations

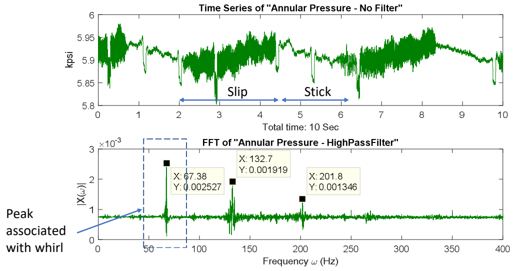


Selective Removal of Noise



Pressure Response During Whirl Vibrations

- High frequency pressure fluctuations observed during whirl vibrations, for both internal and annular pressure



Conclusions

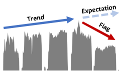
- Inadequate information on downhole dysfunctions is a real drilling performance limiter
- Data transfer, storage, and processing capacities currently are limited
- Finding the right balance between
  - Inadequate sampling rate, just enough to capture phenomena
  - Data overflow, not more than necessary
- Downhole measurements are interlinked
- Differentiation of root cause of measurements by frequency
- Combination of measurements and selective filtering of ‘noise’ frequency ranges

- *Publishing application specific data requirements*
  - Hopefully more examples will follow

Downhole Data To Improve Surface Processes

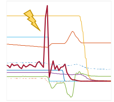
Monitoring ***changes*** in surface to downhole ***transfer functions***

- Surface Data: Primary Source
- Downhole Data: Shown if differs from expectations



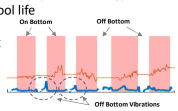
Understanding effects of ***surface actions*** on ***downhole forces***

- Negative or positive effects of surface processes, e.g. during ***connections***



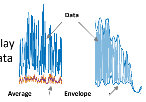
Recognizing the importance of ***off-bottom events*** on tool life

- Focusing on time based data



Investigating multiple **data aggregation** methods

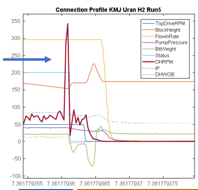
- Not enough resolution to display high frequency data
- Averaging covers important events
- Envelopes



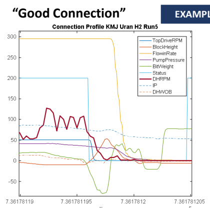
Connection Practices: Impact Downhole

"Bad Connection"

high RPM spike



"Good Connection" EXAMPLE



- Downhole data reveals bad practices of operations
- Using downhole data to understand implications of actions on surface
- E.g. time of pump shut in and picking off bottom
- Implementation of good practices

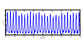
Measurement tool was placed above the motor – essential information for analysis

Automated Vibration Classification

Example for machine learning application – naïve Bayes classifier

Patterns to identify stick slip and whirl:

Raw Data → Feature Extraction → Trained Algorithm → Classification



	RMS	Min	Freq
1	7.1	0.2	22
2	7.3	0.1	28

$P(v_1|D)$
$P(v_2|D)$
...

Whirl | Stick Slip

Confusion Matrix: Stick Slip

		Visual/Manual Classification: No Stick Slip	Visual/Manual Classification: Stick Slip
Model Classification	No Stick Slip	51	4
	Stick Slip	6	39

Confusion Matrix: Whirl

		Visual/Manual Classification: No Whirl	Visual/Manual Classification: Whirl
Model Classification	No Whirl	54	0
	Whirl	6	15

- 250 high frequency sequences of a 90 hours bit run
- 16 features extracted from each sequence
- Split in test and train data
- Trained Naïve Bayesian classifier could correctly identify more than 90% of stick slip and whirl

Barrier: Downhole Data Sensor Errors

- Sources
  - Temperature
  - Pressure
  - Shocks
- Prevention
  - Sensors rated for given environment (more expensive, larger)
  - Cushioning of sensors
  - Pressure resistant housing
- Mitigation
  - Auto-correction
- Semi-Manual correction
  - E.g. taring procedure at every connection

Source: Input from Nii Ahele Nunoo and Alamzeb Khan (NOV), will be published at upcoming conference

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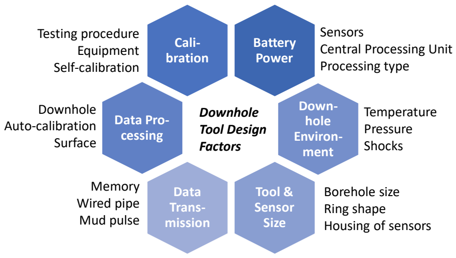
Downhole Measurement Tool Design Factors



- Tradeoffs between design factors
- More precise requirements would help to design better sensors

Source: Input from Nii Ahele Nunoo and Alamzeb Khan (NOV), will be published at upcoming conference

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Baby Steps: Algorithms For Auto-Correction

- Current research focus
- Developed correction algorithms
  - Accelerometers
  - Adequate WOB/TOB correction
    - Often reason for bad WOB readings
    - Possibly eliminate taring procedures
    - More accurate
  - Auto-align downhole and surface data
- Correction algorithms
  - are fairly simple,
  - use known procedures and physics
  - corrections are not purely data based
- Automated vibration classification

Hidden Information
- Found indirect surface measurement for downhole pressure losses, in 'standard' data, no additional sensors required.
- Under development
- Data is underused!
- Explore hidden information

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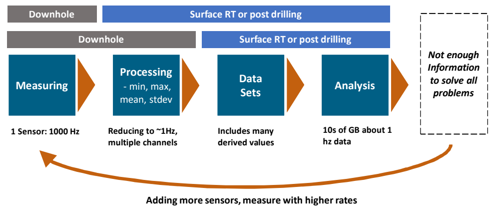
Smarter Data Processing Required



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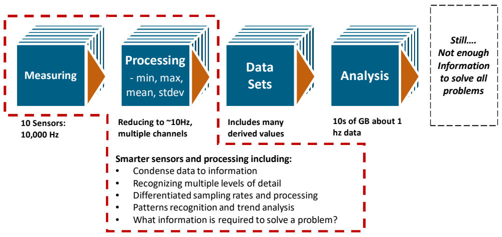
Smarter Data Processing Required



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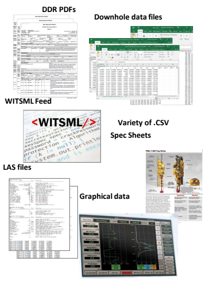
Data Structures, Metadata and Transfer

Structural and process with downhole data



- ***UT project:*** Undergraduate students analyze operator's drilling data supervised by graduate students
- > 80% of time spent on data processing
  - Data in various files and formats
  - 10 GB files too large to open
  - Wrong time stamps
  - Header name is only information on channel
  - Different companies / sensor measure different things – no comparison
- *→ Combining downhole data requires coding and data analysis skills*
- Learning curve for a single project, but not transferable
- Isolated one off solutions

Structured Data: Prerequisite for Automation

- Interoperability, machine readability, comparability of data are essential for automation
  - How do we get there?
  - Tradeoff between standardization and 'progress', agreement on common structures seems unrealistic

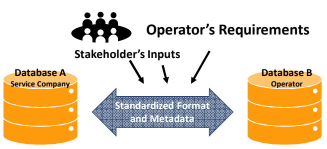
Lack of...

- Standardization
  - One off projects
- Transparency
  - Proprietary tool setups
  - Derived data
- Metadata
  - Critical descriptive information
- Connections to other data

Prevents...

- Learning curve from data
  - Rapid deterioration of data value with time
- Knowledge transfer
  - Data acquisition and analysis are done by different groups with little overlap
- Sharing of data for effective data analytics solution
  - Within companies
  - With 3rd parties

Standardized *Format* for Downhole and Metadata



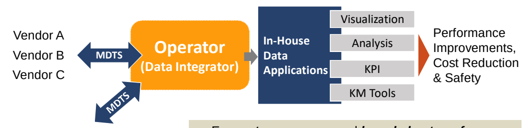
UT defined transfer standard:

- Expanding idea of WITSML to downhole data
- Adding metadata to the files
- Interim solution until it can be taken over by energistics or another group

- <u>Automation of Analysis</u>
  - Managing data loads and integration
  - Standardized formats
  - ***How*** to deliver
- <u>Transparency</u>
  - Enables data analysis
  - Knowledge transfer
  - ***What*** to deliver

SPE 178900

Standard Data Transfer – Business Case for DH Data

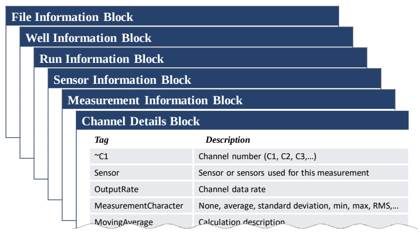


- Ensure ***transparency*** and ***knowledge transfer***
- Use vendors with ***vendor neutrality***
- Vendor independent ***automated analysis***
- ***Minimize time lag*** between collection, transfer and integration of data
- Service companies ***increase business*** with value add

Metadata - Header Section Structure

Above the actual data, the *metadata header* contains 6 basic blocks.

The block structure helps to capture information most efficiently and avoid repetition.



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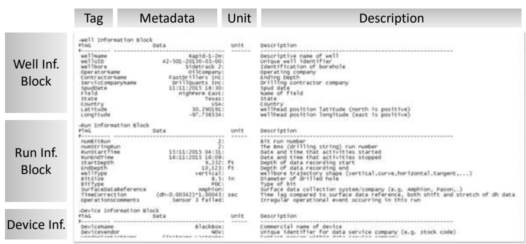
Example of MDTS file format



- Metadata has standardized structure and description, is helpful to data scientists without drilling knowledge

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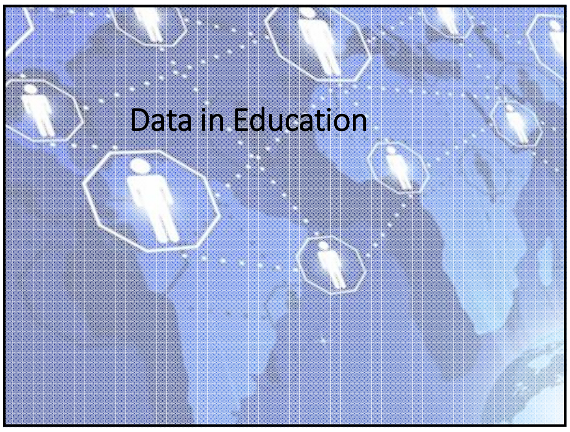

Digitization Strategies in Education

SPE/IADC-184739-MS

Future Workforce Education through Big Data Analysis for Drilling Optimization

Y. Zhou, T. Baumgartner, G. Saini, P. Ashok, and E. van Oort, The University of Texas at Austin; M. R. Isbell and D. K. Trichel, Hess Corporation

This paper was prepared for presentation at the SPE/IADC Drilling Conference and Exhibition held in The Hague, The Netherlands, 14–16 March 2017.

Traditional	New Requirements
• Competition • Individual efforts • Single number answers • Simplifying assumptions • Universal Truths	• Collaboration • Team work (disciplines dissolve) • Dealing with uncertainty • Understanding complexities • Continuous improvement

SPE 184739

Conclusions

- Artificial Intelligence won't magically solve our data problems!
- Results can only be achieved by hard work
  - Definition of data requirements and data structures
  - Unified classifications
- Defining and publishing data requirements for every research project or study
- Big data: Make data comparable across many wells
  - Apply same aggregation methods: 1 minute data is not comparable to 1 second data
- Eliminate manual efforts on data
  - Short term solutions: Correction algorithms
  - Long term solutions:
    - Improve transparency and communication protocols
    - Communicate requirements and improve collaboration with sensor supply chain (tool & sensor manufacturers)
- Prepare workforce for a world of data
  - Years of experience vs. making sense of data

Questions?

THANK YOU TO

RAPID RIG AUTOMATION
Performance Improvement in Drilling

SPE International
Drilling Systems Automation Technical Section

- Data Quality Assurance Group
- Operator's Group

THE UNIVERSITY OF TEXAS AT AUSTIN

Feature extraction for time based data

- Feature Data Set: Each row represents one burst window

Index	TimeHrs	Min	Max	Diff	Std	Var	Avgmin	Avgmax	AvgDifferenc	Avg	FrquPeak1	PeakAmp1	FrquPeak2	PeakAmp2	PeakDista	SS Classifier
217	79.60283	2.318717	11.08021	8.761497	2.300812	5.293736	3.012664	8.556522	5.543857747	5.1392952	0.2929688	0.9831069	31.054688	0.3062997	30.76172	1
218	79.95283	2.318717	9.71123	7.392513	1.665648	2.774384	3.061449	6.720569	3.659119991	4.6305745	30.664063	0.4759945	0.5859375	0.3281791	30.07813	1
219	80.30283	1.771123	7.794653	6.02353	1.26078	1.589565	3.109111	6.071569	2.962457732	4.3585838	0.390625	0.2732926	30.273438	0.2555466	29.88281	1
220	80.65284	2.592513	6.699465	4.106952	0.917132	0.84113	2.86631	5.379266	2.512955746	4.079922	0	0	0	0	0	1
221	81.00284	1.771123	13.54438	11.77326	2.332939	5.442604	4.617897	9.437433	4.819536378	4.986088	30.078125	1.7481684	60.644531	0.5606203	30.56641	0
222	81.35284	2.318717	12.4492	10.13048	2.766703	7.654647	3.003071	10.98895	7.985877098	5.6232563	0.4882813	0.8771709	30.175781	0.4112714	29.6875	1
223	81.70284	2.592513	3.140107	0.547594	0.08499	0.007223	2.592513	2.87371	0.281196775	2.8693136	0	0	0	0	0	0
224	82.05284	2.318717	3.140107	0.82139	0.124881	0.015595	2.592513	2.775044	0.18253124	2.6603316	0	0	0	0	0	0
225	82.40284	1.771123	12.1754	10.40428	1.433764	2.055679	3.159018	6.973262	3.814244014	4.3052055	26.074219	0.3896454	0	0	0	1
226	82.75284	2.318717	12.4492	10.13048	3.146943	9.903248	2.887962	11.08021	8.192251664	5.7841037	0	0	0	0	0	1
227	83.10284	1.497326	13.81818	12.32086	2.882047	8.306192	4.135732	10.62389	6.488154247	5.1308582	25.976563	2.2811058	51.757813	0.3985125	25.78125	0
228	83.45284	2.04492	10.25882	8.213904	2.075463	4.307547	3.961497	7.977183	4.015686111	4.9429264	30.175781	2.4916605	60.351563	0.4908214	30.17578	0
229	83.80284	1.771123	11.9016	10.13048	2.568155	6.595423	2.86631	9.163636	6.29732635	5.1570482	25.292969	1.7624431	50.488281	0.6653496	25.19531	0
230	84.15284	2.04492	11.9016	9.856685	2.38431	5.684932	3.231373	8.232727	5.001354767	5.1297408	26.074219	1.9646024	51.464844	0.3861104	25.39063	0
231	84.50284	1.771123	16.82995	15.05882	3.003653	9.021932	3.030588	9.333012	6.302423909	5.3476942	0.390625	0.6426452	26.171875	0.5128825	25.78125	1
232	84.85284	1.497326	15.46096	13.96364	2.619836	6.863541	4.297508	10.44136	6.14384683	5.2999575	29.6875	1.3220823	0	0	0	1
233	85.20284	2.04492	10.80642	8.761498	2.268915	5.147975	2.86631	7.1923	4.32598953	5.1114325	29.882813	2.7187567	59.765625	0.6308048	29.88281	0
234	85.55284	2.04492	14.09198	12.04706	2.564293	6.5756	2.318717	10.53262	8.213903462	5.268435	26.464844	1.0279136	0	0	0	1
235	85.90284	2.04492	11.08021	9.035294	2.242654	5.029498	3.048841	5.297593	2.248751411	5.1214193	29.6875	1.8266491	58.886719	0.1557829	29.19922	0
236	86.25284	2.04492	13.27059	11.22567	2.136537	4.564789	3.140107	6.408128	3.268020929	4.814201	30.371094	0.677655	0	0	0	1
237	86.60284	2.318717	11.62781	9.309091	2.317844	5.372401	3.140107	8.25098	5.110873161	5.1698321	30.371094	2.490172	60.839844	0.6370876	30.46875	0
238	86.95284	1.771123	12.1754	10.40428	2.645531	6.998836	2.592513	6.760309	4.167795845	5.3088727	26.171875	1.8307148	52.441406	0.6326086	26.26953	0

Stick Slip Classifier: 1 means that stick slip is present, 0 means that there is no stick slip present

Features

1. Minimum
2. Maximum
3. Delta Max Min
4. Standard Dev
5. Variance
6. Average Min (running avg)
7. Average Max (running avg)
8. Delta Average
9. Average
10. Frequency and Amplitude of FFT Peak 1 and 2 (4 features)
14. Peak distance of FFT