MFL RESULTS LIKE A LASER SCAN – TAKING ANALYSIS OF COMPLEX CORROSION AND PINHOLES TO THE NEXT LEVEL

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Abstract

3D LASER SCANS are becoming increasingly popular for field verifications, and pipeline operators are demanding a corresponding ultra-high-resolution inline inspection technology capable of producing refined integrity calculations.

Ultimately, such an ultra-high-resolution inline inspection technology would lead to improved pipeline safety while simultaneously reducing the need for costly field verifications.

Hence, an ultra-high-resolution MFL technology with sensor spacing similar to that of a 3D laser scan has been developed.

In order to provide reliable inspection results using a ultra-high resolution MFL measurement system, a series of challenges had to be overcome:

- The extremely tight track spacing requires continuous data recording without any gaps in circumferential direction. This calls for accurate mechanical design to ensure each sensor stays exactly in its track, especially when passing welds.
- There can be a significant impact on the recorded data quality due to sensor placement on the yoke in relation to the magnetic field. Specific normalization efforts are required to ensure a uniform appearance of data for subsequent evaluation.
- The sheer amount of inspection data generated warrants the use of machine-based learning algorithms in data evaluation, reducing the ‘human factor’ impact.

In addition to presenting solutions for the above listed technical challenges, this paper will also provide insight into how pipeline integrity management will benefit from ultra-high-resolution MFL inline inspection results.

Introduction

ONE OF THE BIGGEST CHALLENGES that pipeline operators face is managing the integrity of pipelines containing certain difficult-to-assess defect types, such as: pinholes of one millimeter (0.04 inch) and less in diameter, highly corroded pipelines with complex corrosion, microbial corrosion (MIC), top-of-the-line corrosion (TOLC) and certain girth weld defects.

The reliable detection and sizing of these kind of defects have historically been beyond the capabilities of MFL-based inline inspection systems. The small surface dimensions and the resulting limited volume of metal loss have been insufficient to generate a significant magnetic flux leakage signal.

Given today’s market situation, including the corresponding pressure on operators’ integrity budgets, and the growing public awareness of the oil and gas industry, there is a strong desire to find more effective and reliable ways to perform the most accurate integrity calculations possible. These would lead to less conservative assessments, meaning less field verifications and a reduction in repair cost, while making no compromise on safety and compliance. These pipeline operators’ needs were the key drivers for ROSEN to start a research project with the target to build an MFL-based ILI tool with the highest spatial resolution that is technically feasible.

Technical Solution

TO MAKE THIS POSSIBLE, three things had to take place: new sensors had to be engineered and developed, the mechanical properties of the ILI tool had to be enhanced to ensure perfect sensor positioning across the entire pipeline, and new algorithms for tool calibration and data evaluation had to be conceived.

The new sensors feature three-dimensional integrated circuit modules that enabled the development team to place fully triaxial MFL sensor elements within a circumferential track pitch of only 1.6 millimeters (0.063 inch), thereby more than doubling the resolution of current standard MFL technologies. Combined with a one-millimeter (0.04 inch) axial sampling, this essentially allows MFL-based inline inspection to move from individual data points to true Pipeline Imaging™, an example of which can be seen in figure 1.

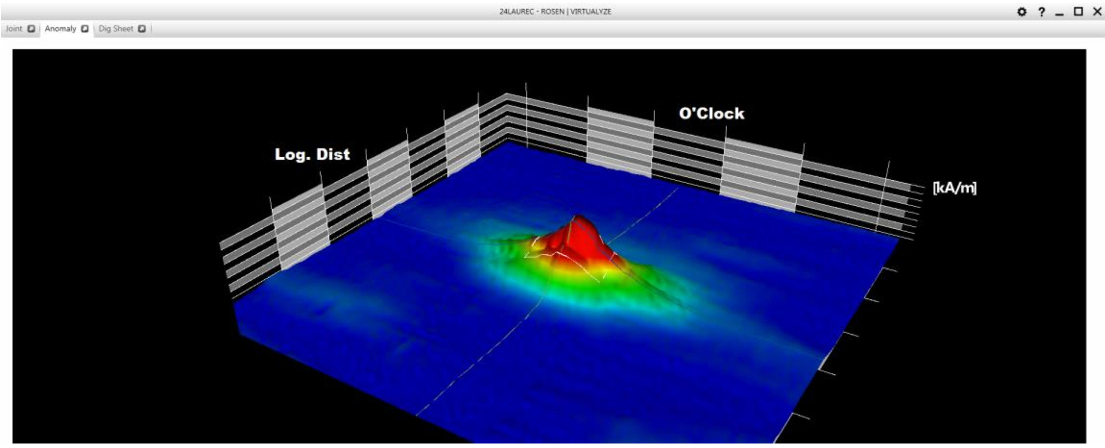

Figure 1. Example of 3D MFL-A Ultra data visualization

During the course of the development, it soon became clear that simply improving the sensitivity and resolution of the sensors would not be sufficient to deliver the demanded resolution.

Traditionally, sensor carriers are placed on one sensor ring and are located, at a minimum, two mm (0.08 inch) apart because of mechanical constraints. In this case, to achieve the desired resolution, two sensor rings had to be implemented beside one another, and the carriers mounted in a slightly offset fashion, as can be seen in picture 1.

Picture 1. Dual sensor ring of MFL-A Ultra ILI tool

However, during the extensive research and development process, it became clear that this in itself would present a challenge due to the ultra-high resolution and the elevated sensitivity of the individual sensor elements. These are affected by their physical location within the magnetic field of the yoke as the displacement of approximately the width of the sensor rings already had a significant influence on the measurement results. In response to this, essentially two data sets are generated, one measuring closer to the front and one closer to the back of the magnetic field. Using image processing algorithms, these sets must then be normalized in order to create one triaxial magnetic image for the pipeline. Figure 2 shows the data sets before and after normalization, the left depicting the separated data sets from each sensor ring and the right displaying the combined image.

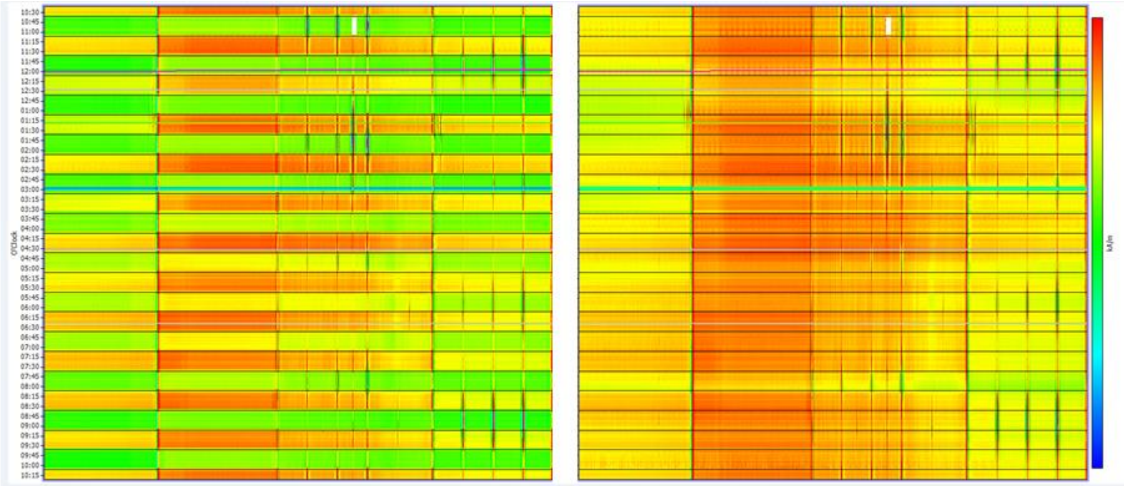

Figure 1. Before (left) and after (right) the normalization of data sets from both sensor rings

In summary, only a dual sensor ring approach ensures full ultra-high-resolution circumferential coverage in all operational situations.

These developments enabled the creation of a 8” prototype tool that has already performed several successful runs in the field. Using this tool, the team achieved detection of pinholes down to one millimeter (0.04 inch) in diameter.

Data Evaluation

AN APPLICATION FOR BIG DATA TECHNIQUES are the 2.5 TB of data that have been collected during a 300-kilometer run (180 miles) by the second tool of this series, now in 24”, with a speed control unit (SCU) and XYZ mapping capabilities to be ready for commercial applications. Next to a fast and reliable on-site data quality check, new algorithms and processes had to be developed in order to handle the huge volume of potentially integrity-relevant indications.

To achieve the market-unique performance specification of this service, adaptive algorithms based on machine learning are fed with 3D high-resolution laser scans from real life pipeline defects. This AutoData™ algorithm suite is engineered to ensure a consistent automated data management across the entire service, spanning from service calibration and data preparation to defect detection, classification, and sizing. It is geared towards delivering Pipeline Imaging™ on all defects, instead of merely on a certain selection of features per kilometer or mile.

Often when deciphering raw pipeline data, irregularities may occur that do not necessarily impact the integrity of the pipeline. These include various installations, that can often take quite some time to identify. Therefore, the AutoData™ system has been designed to classify these installations using algorithms of machine learning (AML), which learn from data and make calculations about unseen data. They have the ability to learn from examples without being explicitly programmed for a given task. Classification of unknown data is based on known properties learned from the training data.

The applied detection algorithms both for pipeline installations and anomalies yield a considerable amount of possible locations to look at, where 200,000 to two million is not uncommon even for small lines.

The number of locations which are actually important to pipeline operators varies in this set, depending on the pipe conditions. The overall amount of possible locations cannot be evaluated by the data evaluator within a reasonable timeframe. Furthermore, each pipeline has its own characteristics due to outer circumstances, which yield different signal shapes from line to line.

In order to overcome this issue, one needs to exploit the data redundancy, adopt the knowledge of experienced data analysts and convert this into a suitable prediction system.
The basic assumption is that a small subset of pipeline installations or anomaly representatives are necessary to evaluate the whole pipeline. This assumption is supported by the evaluation experience that ILI data signals from a similar source (e.g. welds from the same pipeline) also have a similar data shape.

Figure 2 illustrates this observation for pipeline installations. Each point represents a high-dimensional characteristics vector as a description of a location in the pipeline. The axes values are of arbitrary value but their relative position to each other are of importance [Maaten2008]. Clustering points indicate a similar signal shape whereas points far away resemble differences in shape. Figure 2 was chosen in a low dimensional representation for this kind of point cloud because humans lack the ability to grasp four and more dimensions. In fact the overall complexity of such a point cloud cannot be visualized by the human eye.

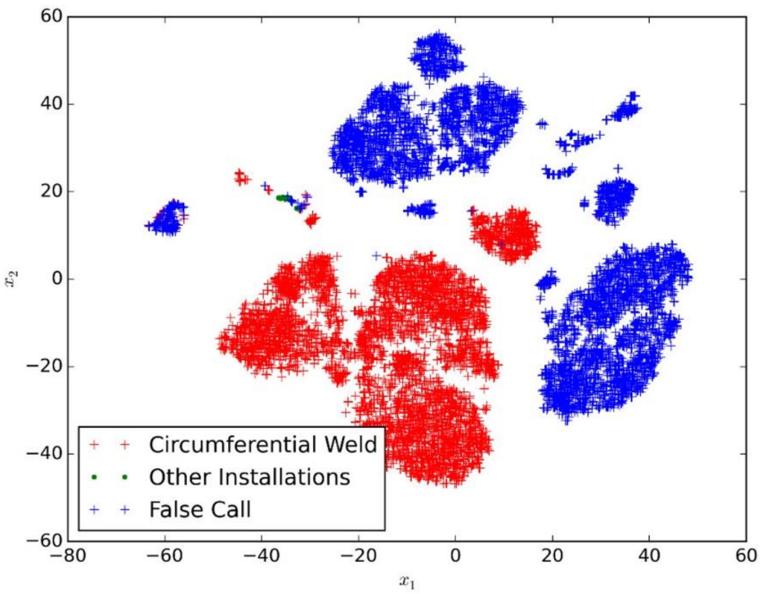

Figure 2. Appearance clustering of pipeline installations for an example pipeline

In Figure 2, most of the signal classes cluster well but a few of the smaller groups are a mixture of different pipeline installation classes. The "false call" class are locations that were detected by the applied signal search algorithms but are not important to the pipeline operator, and need to be filtered out. For a pipeline installation evaluation, only a small number of representatives of the bigger clusters must be labeled while the smaller mixtures need special attention of the Data Evaluator. The process of finding these representatives and classifying the remaining set is known as "Active Learning" [Settles2009] in the machine learning field.

Figure 3. AutoData™ workflow overview

In Figure 3, the workflow of AutoData™ is illustrated. Starting from the ILI data (1), a pre-processing step (2) includes searches both for pipeline installations and anomaly indications. For each possible indication, a set of characteristics, whose importance may vary from pipeline to pipeline, is extracted.

The characteristics are used in the Active Learning phase (3) as the input for the machine learning algorithm, and comprise pre-designed properties like the maximum amplitude or the signal shape. The algorithm selects a representative sample from the set of available indications and the data evaluator assigns a label to this presented element. With this information, the algorithm can infer the labels of the remaining indications and presents a new representative to the Data Evaluator.

Next, a QA/QC step (4) is performed by the data evaluator using an interactive overview over the whole pipeline and the decisions made by AutoData™.

Gaining enhanced reporting times is one positive effect of bringing automation into data evaluation. As well as the reduction of the human factor and therefore enhancing the output quality of the report (6). Results become repeatable and reliable, as the level of automation is increased. Results are finally supervised by a data evaluator ensuring QA/QC. Furthermore, a continuous improvement loop (6) was setup for AutoData™ to ensure that the results are fed back into the research and development center. The results are used to further train the algorithms on a continuous basis.

Summary

MAJOR BENEFITS FOR PIPELINE OPERATORS are delivered by this new technology, or more precisely the great leap forward for a reliable and dependable technology. It now provides the highest ILI resolution available to date. The data collected delivers highly accurate Pipeline Imaging™, making sure no integrity-relevant defects are missed. This delivers a detailed yet solid foundation for more accurate feature boxing and river bottom profiles (RBP).

These allow for less conservative failure pressure calculations and estimated repair factors (ERF). Ultra-high resolution provides higher accuracy, hence smaller error bars. It also delivers more features, including many smaller ones, and breaks down some larger features into several smaller ones. The latter then often have a smaller effective area, as can be seen in figure 4.

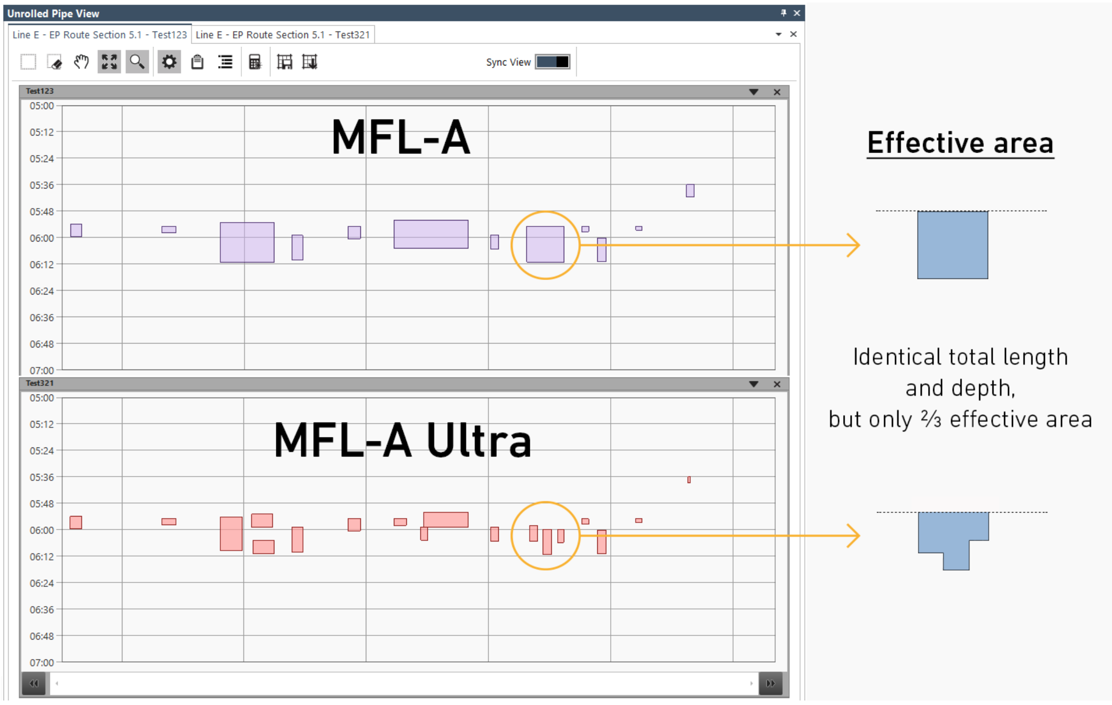

Figure 4. Effective area reduction through MFL-A Ultra

This subsequently leads to less features above the critical repair threshold, meaning less field verifications and a reduction in repair cost, while making no compromise on safety and compliance.

One of the most important additional benefits that the detailed imaging of the features will provide is better diagnosis of the cause of features. As in medical imaging, the more detailed the view integrity engineers have of the features the better they are able to diagnose the cause, for example pre-commissioning damage or microbially induced corrosion, and whether they are benign or active. Once the 'disease' is known, the appropriate 'treatment', be it repair, inhibition, biocide treatment, cathodic protection upgrade, recoating, enhanced cleaning, or monitoring by repeat inspection, can be 'prescribed'.

The first series of runs of this technology have been the first step in delivering real Pipeline Imaging™ instead of mere line plots and C-scans. Plus, it runs in common MFL operating conditions in terms of velocity, passage, temperature, pressure etc. This technology is perfectly geared for both the detection of very small pinholes and the structural analysis of heavily corroded pipelines with pit-in-pit/complex corrosion, MIC, top-of-line-corrosion and girth weld defects.

Taking a look beyond what is possible now, it is also foreseen that selected improvements made for the MFL-A Ultra technology will also benefit the traditional high-resolution MFL technologies in the mid-term.

References

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[Settles2009] Burr Settles: Active learning literature survey. Computer Sciences Technical Report 1648, University of Wisconsin-Madison, 2009