CAAP Final Report

Date of Report: August 22, 2017

Contract Number: DTPH5614-H-CAP06

Prepared for: Department of Transportation

Project Title: Robust Anomaly Matching for ICIPs: Reducing Pipeline Assessment Uncertainty Through 4-Dimensional Anomaly Detection and Characterization

Prepared by: Colorado School of Mines

Contact Information: Craig Champlin, cchampli@mines.edu , 303-653-3004

For year period ending: September 30, 2016

Business and Activity Section

(a) Generated Commitments -

I. Agreement Changes

A. Requested a no-cost extension from March 31,2016 to August 31, 2016

II. Purchases

A. Tubing for surrogate-pipe test fixture --- $45.20

B. Lighting for test fixture - $32.00

(b) Status Update of Activities -

I. **Kickoff Meeting**: Held at CSM, October 6, 2014. Jim Merritt and David Mulligan from DOT and John Steele and Craig Champlin from CSM were in attendance. A presentation on the research to be conducted was given, and the DOT managers gave us advice on how to be most effective in producing useful results.

II. **Experimental Setup:** Initial work on the CSM Experimental Lab Test Setup for surrogate pipe integrity sensor data has been underway.

III. **Data Collection:** We have been able to collect data using the CSM Experimental Lab Test Setup using a surrogate pipe. Data were collected under variable conditions with two different types of sensors. All tests were run with randomized scan velocities. Data quality was sufficient for testing our feature detection algorithm.

IV. **Algorithm Implementation:** The feature detection algorithm was adapted to match locations both with and without odometry data. The algorithm with odometry is robust to tool velocity surges such as those that sometimes occur during real pipeline inspections. However, exact odometry is not required. Even "poor" odometry gets the algorithm close

enough to the correct location to be sufficient. We have also implemented a similar approach that does not rely on odometry.

V. **Algorithm Results:** We have constructed an artificial pipeline "run" consisting of five pipeline "segments". Three segments in the "run" were featureless. Two segments contained synthetic "defects" - various sized holes drilled through the cardboard "pipe". Scans were taken with a laser. In one set of experiments, the holes were open and deep. In the second set of experiments, the holes were covered and were a close match to the background intensity. Our sensor, a scanning laser, traveled down the pipe, collecting data over 240 degree arc. Multiple data sets were collected from these two different configurations, with variations in the travel velocity of the sensor (to simulate real-world conditions). These set were then laced together to give sections of pipe that were 5 segments long. The algorithm was run on these 5-segment "runs". The goal was to see if the algorithm could match up the features from the two different appearances.

A. With minimal optimization of the algorithm, we were able to achieve the following location matching rates:

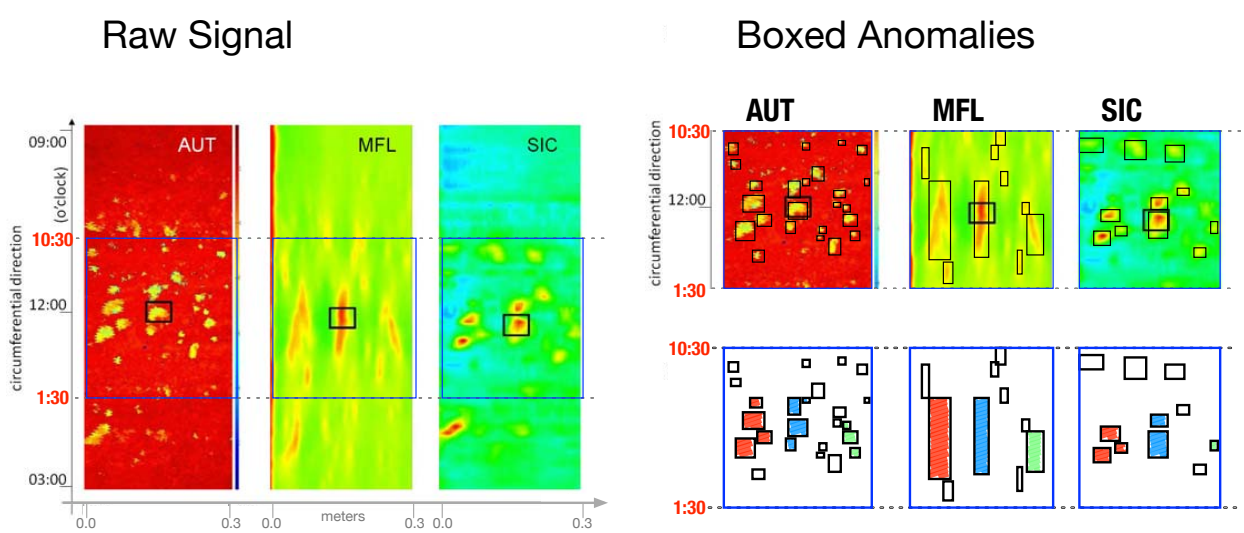
1. True positive: 80.3% - locations correctly identified as equivalent in two different data sets

2. False negative: 15.7% - locations incorrectly identified as not matching

3. False positive: 3.9% - locations incorrectly matched

B. These preliminary results are encouraging. While the artificial holes are distinct, they are sparse. Additionally, there were long sections of featureless pipe that were virtually indistinguishable. We were able to achieve good matching (alignment) over these regions.

VI. **Boxed and Called Out Anomaly Algorithm:** In conjunction with One Bridge Solutions, we developed an algorithm which is able to associate boxed and called out anomalies across traditional inspections. When vendors box and call-out an anomaly, they discard most of the information about that anomaly. This makes it difficult to uniquely identify anomalies, consequently making anomalies difficult to match when there is moderate to high anomaly density. (Matching anomalies is trivial when there are only a handful of anomalies per joint.)



Signal Differences: [Left] The raw signal of three sensors showing the in the top 60º over the same 0.3 meter section. (From: (Huyse 2010)) **[Right]** The raw signal in the top 30º (between 10:30 and 1:30) of the same 0.3 m long section of pipe. For the top set we have overlaid bounding boxes onto each anomaly. For the lower set, we have removed the raw signal to show just the boxes.

A. Anomaly descriptor: Much of our work was focused on creating a computer feature descriptor for machine learning which could identify matching anomalies across two inspections having a moderate to high density of anomalies. Our descriptor describes shape and position. We use the coordinates of the anomaly centroid, the length and orientation of the diagonal of a bounding box, and the depth.

B. Clustering: Our analysis revealed that in pipe segments with moderate to high anomaly density it is rare to see a 1:1 anomaly correspondence across multiple inspections. It is common to see a single large anomaly in one inspection represented as multiple smaller anomalies in a second inspection. To account for this we implemented a spatial interaction pyramid whereby we generated aggregate anomaly descriptors whenever anomalies were within a configurable distance from one another. We considered these anomaly clusters as individual anomalies so we could match across different inspection reporting thresholds. We retained the identities of the constituent anomalies within these aggregate anomalies such that after matching we could correctly identify the individual anomalies required to make a single match.

C. Matching: Our anomaly matching algorithm relied on an early Bayesian matching algorithm called Relaxation matching. This older algorithm was developed for navigating in space using a pre-known star chart. We fed the feature descriptors for both the original anomalies and the aggregate anomalies into this algorithm to find the best matches. When an aggregate anomaly gets a better matching score than individual anomalies, we say that the aggregate anomaly is a match and discard the individual matches comprising it.

The algorithm makes an initial best guess using a Bayesian matching scheme to find the best matches. This step is very fast. Next the algorithm repeats this process for every anomaly in the set. For each anomaly it calculates what would happen if that anomaly were NOT in the set. If the score improves without a match, then that match is removed. This is called the "relaxation step". This step is slow but thorough.

D. Results: Our anomaly descriptor and clustering approaches are sound in the the face of moderate to high anomaly densities. We were able to achieve high match rates which matched our intuition about when an aggregate match would be better than an individual match. See the figure above.

(c) Description of any Problems/Challenges -

I. **Universal access to pipeline inspection data**

A. We were not successful in convincing a pig vendor to supply us with the raw signal directly from pig sensors. Our best chance was some Chevron-owned data which was collected by Rosen. Although Chevron "owns" the data, in that they are able to generate graphs of this signal using Rosen-supplied software, Rosen would not supply Chevron the structural parameters of the data file so that Chevron could construct their own processing software using this same raw signal.

B. A number of phone calls showed that other vendors are just as unwilling to give the operator the raw data concerning their pipelines. By raw data we mean the signal directly from the sensors. Instead of supplying this signal, vendors deliver a set of boxed-and-called out indications.
C. The process for boxing anomalies is subjective and discards a tremendous amount of information about individual defects. Because each vendor makes different choices about how to to box anomalies, an operator is unable to use a standard algorithm across several inspections. Since the signal is hidden, the operator is unable to make their own algorithm. This is a problem.
D. This reluctance of pigging vendors to release their data to operators will hinder operators' ability to develop time-dependent pipeline analytics which process the data from multiple inline inspections. This will cripple the industry's ability to leverage multiple inspections to learn location-specific corrosion and crack growth rates.
E. This is unfortunate. It would greatly benefit the industry if PHMSA could intervene to support the development of multi-inspection analytics. This will require either a standard algorithm for vendors to use when when boxing and reporting anomalies or it will require that vendors supply the data structure of the data files which pipeline operators have purchased.

II. Access to ICIP data

A. SIG ran a sequence of test runs with their integrated cleaning and inspecting pig (ICIP). We were promised this data, but it was never delivered to us due to an intellectual property lawsuit between SIG and Chevron. As such we were never able to test our algorithm against this data.
B. As the project finished, we were able to get some data from I2I's ICIP. However, this data was in an unexpected format and arrived too late to be useful for our testing.

III. SLOW boxed-and-called out anomaly matching

A. The relaxation matching algorithm relies on one sub-iteration for each anomaly in the match set. One must run through these sub-iterations multiple times until the algorithm converges. We do this relaxation step to eliminate weak matches. While this is still faster than matching by hand, it is slow. In our testing, two inspections of moderate anomaly density took over a week of computer time to process. This needs to be improved. The first step of the algorithm, the Bayesian matching step, is very fast. It gives us hope that other probabilistic methods will work.

(d) Planned Activities for the Future Projects

***I.* Algorithm for matching raw signals:**

A. We would like to explore our raw signal matching algorithm in more detail by using real raw signal data (vs our synthetic data) to do a comparative study of the parameters of the algorithm.

1. We would like to answer questions about the best way to construct the difference cube and what are the best ways to select paths through this cube.

    2. We would like to compare different techniques for generating a base image from raw signals. What is the best way to attenuate the raw signal to compare a wide range of inspection types? Can we establish a technique technique which works well across both high resolution and ICIP using many sensing types? (MFL, eddy current, AUT, etc.)
  B. We would like to use our signal matching algorithm for higher level studies. For example our motivation for developing this algorithm was to be able to directly measure individual corrosion growth rates. We would like to use our algorithm for this purpose.

II. **Algorithm for matching boxed and called out anomalies:**
  A. We would like to apply a graph-based technique for spatial matching using the same feature descriptors and aggregate anomalies that we developed here.
  B. We would like to compare the effectiveness of several pattern matching algorithms. Again, we would use the same features and clustering techniques we developed here.
  C. It would be interesting to see if we could use this with raw signal matching

III. **Higher-level analysis - corrosion and crack-growth rates**
  A. We did this work in anticipation of being able to easily combine multiple pipeline inspections. Our goal is be able to see time-dependent signals emerge. We hope to directly measure corrosion and crack-growth rates by assembling information from multiple inspections. The work we did here are some preliminary steps. Many questions remain.

(e) Progress against stated milestones

This section recreates the project schedule introduced during the kickoff meeting and describes progress made against each listed item. Progress is in *italics* to distinguish it from original text.

I. Experimental Setup
  A. Build test rig
    1. *complete*
  B. Collect synthetic data
    1. *complete*
  C. Collect data from pipe sample
    1. *this was problematic as described in the problems section*
    2. *relied exclusively on synthetic data, no real data available*

II. Baseline SAM
  A. Adapt CAT-SLAM as a SAM algorithm
    1. *completed*
  B. Test on synthetic data
    1. *complete*
  C. Test on real data
    1. *problematic as described above*

III. Real Data
  A. collect and clean data

    1. *problematic as described above*
  - **B.** Characterize data
    1. *problematic as described above*

IV. Compare SAM and CAM

  - **A.** Identify additional SAM candidate algorithms
    1. *complete - settled on Sequence SLAM*
  - **B.** Implement 2 additional SAM approaches
    1. *complete - Implemented Sequence SLAM*
    2. *complete - Implemented Sequence SLAM with odometry*
  - **C.** Compare SAM algorithms - synthetic data
    1. *complete*
  - **D.** Compare SAM algorithms - real data
    1. *problematic as described above*
  - ***E.*** Final report
    1. *complete*

V. Intern

  - **A.** Chevron Energy Technology Company
    1. *complete*