Advanced Condition Assessment & Pipe Failure Prediction

Optimal management of water infrastructure

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Progress on Activity 2

Automatic Detection of Pipeline Construction Features with RFEC technology

Overview

In-line inspection with Remote Field Eddy Current (RFEC) tools requires detection of construction features such as joints, elbows and off-takes. We propose to automate this process using supervised learning. Firstly, signal processing techniques are used to detect features in the RFEC recorded data, where features in general refer to both defects and construction characteristics. Secondly, a machine learning algorithm is employed to classify all the detected features into construction features or defects. Over 800 meters of RFEC data recorded from the Strathfield research test-bed, established as part of this collaborative project, have been used to evaluate the proposed approach.

Background

Remote Field Eddy Current technique (now known simply as the Remote Field Technique "RFT") is commonly used for in-line inspection to assess pipe condition in large sections of pipelines. An example of such an inspection tool is shown in Figure 1. Detection of construction features, such as B&S joints, flanges, valves and off-takes is a crucial step in the identification of the pipe sections to localise and size specific defects with RFT tools. The process is usually done manually, which results in slow data processing.

We propose to automate this process through the use of machine learning algorithms. Eight hundred meters of labelled RFT data is being used for evaluation. With labelled data we mean that the position of all the construction features along the assessed distance is known a-priori. Supervised learning through a state-of-the-art classifier is therefore applicable to obtain accurate classification of the detected features.

Figure 1. Russell NDE Systems Inc. See-Snake tool used to detect pipeline corrosion, pitting, wall thinning and graphitisation.

Data

The Canadian See Snake owned by Russell NDE Systems Inc, and operated by their subsidiary PICA: Pipeline Inspection and Condition Analysis Corp., is the tool that was used to inspect the test-bed. Data has been provided by Russell Technologies as part of the collaborative research project.

The See Snake technology employs RFT for measuring pipe wall thickness. RFT works by detecting changes in an alternating current (AC) electromagnetic field generated by the See Snake. As the electromagnetic field interacts with the metallic pipe wall, it increases in magnitude at locations where metal loss exists.

The See-Snake tool is configured with 56 channels that provide 360°circumferential information of the pipe on 1mm axial spacing, as recorded by the tool's encoders. The data comprises distance travelled by the tool, amplitude and phase of the RFEC signals, clock location of each channel and Tool tilt within the pipe. Some tools also measure temperature and pressure.

The information on the exact location of the B&S joints, valves and off-takes in the data-set is also available. This information from now on will be referred to as 'ground-truth'.

Data is divided into training and testing sets. The training set requires the data and the ground truth as input. The testing set used to evaluate the effectiveness of the algorithm only requires the data; while the ground truth is only used to compare real and predicted outputs.

Approach

Construction features on the phase and amplitude of the RFT signal are relatively distinct from defects such as wall-loss, permeability variation, pitting, etc. We exploit this characteristic to classify data into two main categories: construction features and non-construction features.

The approach for automatic detection of construction features relies on three steps:

1) Detection of signal peaks. The sum of the normalised phase for all channels is employed to extract peaks and valleys of the signal (see Figure 2).

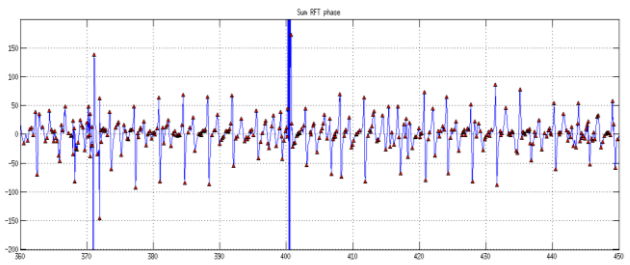

Figure 2 RFT phase signal with the detected peaks and valleys

2) Description of the signal peaks. Signal descriptors characterise the peaks and valleys of the signal. Multiple characteristics of the peaks are concatenated into a single descriptor. The elementary characteristics used are: magnitude, amplitude value at peak location, variances of the signal and its first and second derivative in a window surrounding the peak.

3) Machine Learning Model for classification. In machine learning, support vector machines (SVMs) are supervised learning models that analyse data and recognise patterns, and are used for classification analysis. A basic SVM predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given the training set, the SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is therefore a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible (see Figure 3). New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

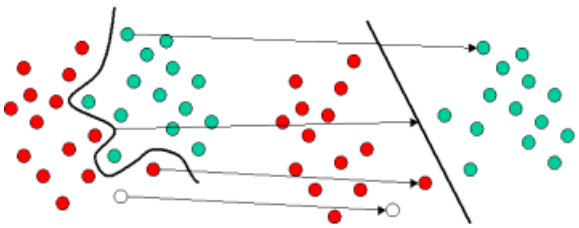

Figure 3 SVM example of the construction of the high dimensional plane that separates the data

The SVM model trained for this work uses the descriptors and the ground truth to learn how to separate construction features from non-construction features. The learned SVM model is later employed to classify construction features in unseen data.

Results

A 3-fold cross-validation test using the training and testing data set attained 98.59% accuracy in classification. The results of evaluating the detection algorithm on the whole data set collected during the trial on the test-bed are shown in the following table:

	No-Joints (Detected)	Joints (Detected)
No-Joints (Real)	2813	17
Joints (Real)	4	221

The total number of real joints found from manual inspection of the ground truth data was 225. The algorithm detected 3055 peaks, where 238 have been classified as joints - 221 of them correctly, 17 incorrectly. A visual example of the detection is given in Figure 4.

Figure 4 Visual imaging representation of the RFT signal on a 100m section (after a river crossing on the test-bed). The joints detected by the algorithm are superimposed in red.

Moreover, the algorithm has been used directly by Russell NDE for testing on unseen data collected from the test-bed. The data was withheld by Russell NDE for their own evaluation of the effectiveness of the algorithm. The algorithm detected 100% of the construction features without false positives, a promising result.

Summary

We have automated the construction feature detection process in Remote Field Technology signals. The algorithm only takes a couple of minutes for an 800 meter data set. This algorithm has shown great potential to improve the manual process currently used to detect pipeline construction features, and to do so with confidence.

Partners

The partners in this research project include Sydney Water Corporation, UK Water Industry Research Ltd, Water Research Foundation of the USA, Water Corporation (WA), City West Water, Melbourne Water, South Australia Water Corporation, South East Water Ltd and Hunter Water Corporation. Monash University leads the research supported by University of Technology Sydney and the University of Newcastle. Other collaborators include Dr Balvant Rajani from Canada.

For information on data exchange for Activity 2 contact uts-water-mains@lists.feit.uts.edu.au