Activity 2: Direct Condition Assessment Methods

Activity Co-leaders: A/Prof. Jaime Valls Miro, Prof. Gamini Dissanayake
UTS

Scope: Innovative Methods for Automatic Interpretation of Data Gathered from Existing Sensors

Key Expected Outcomes:

1. Algorithms for improved interpretation of data gathered from 4 direct condition assessment techniques:
    - (external) MFL
    - (external) BEM
    - (in-line) RFT
    - (in-line) Acoustics

2. Guidelines of relative merits of the technologies evaluated for inspection under common application scenarios

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Activity 2 – UTS Team

Academics (x5):

- Prof Gamini Dissanayake (Co-activity leader)
- A/Prof Jaime Valls Miro (Co-activity leader)
- A/Prof Sarath Kodagoda (Sensor modelling, MFL)
- Dr Alen Alempijevic (Sensor modelling, BEM)
- Dr Teresa Vidal Calleja (Data interpretation, machine learning, estimation theory)

Fully dedicated (funded from project) personnel (x5):

- Buddhi Wijerathna (PhD candidate) – Thesis submitted Sept'15
  - Magnetic Flux Leakage modelling (AIA)
- Nalika Ulapane (PhD candidate) – Thesis submitted Sept'15
  - Broadband Electromagnetics modelling (RSG)
- Daoblige Su (PhD candidate)
  - Acoustics modelling and localization (Pure/Aqua Environmental)
- Raphael Guenot (PhD candidate)
  - Remote Field Technology modelling and localization (Russell NDE/PICA)
- David Hunt (Technical Assistant, Sept'15 – Mar'16)

Note:

Buddhi Wijerathna and Nalika Ulapane have also been temporarily appointed as Research Associates for ~1 day/week since March 2015

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Engagement with Technology Providers

- Rock Solid Group* (BEM)
- Asset Integrity Australia* (Advanced Engineering Solutions Ltd) (MFL)
- Russell NDT Technologies/PICA (RFT SeeSnake)
- Pure Technologies Ltd* (Acoustic Sahara@PWA)

* Australian partners

Presentation Outline

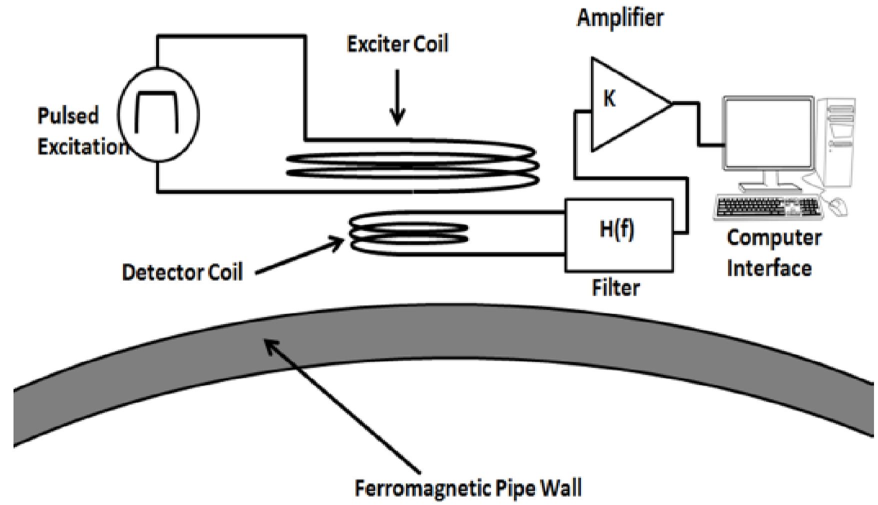
1. Latest research **progress** since last TAC
   - Rock Solid Group (BEM)
   - Asset Integrity Australia (Advanced Engineering Solutions Ltd) (MFL)
   - Russell NDT Technologies/PICA (RFT SeeSnake)

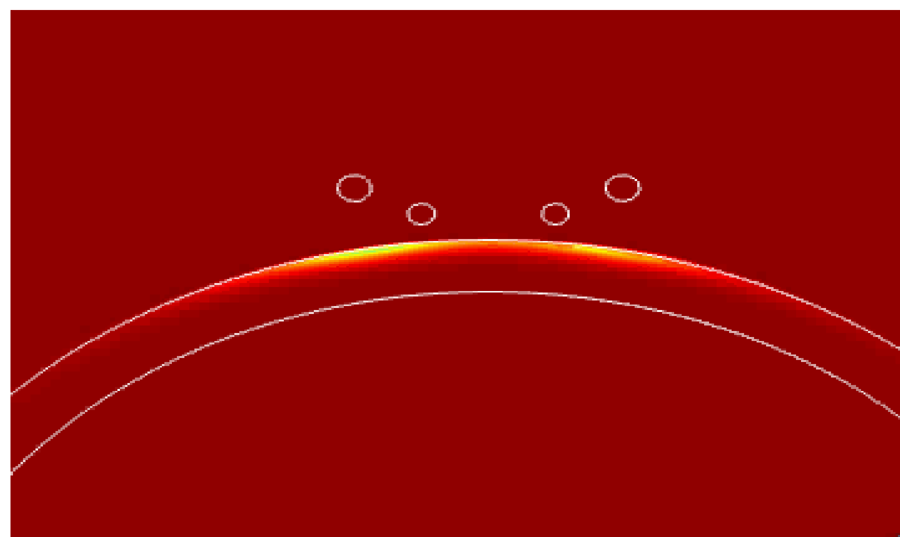
2. What have we learned **so far** about MFL, BEM, RFT and Acoustic PWA for the purpose of failure prediction

RSG (BEM): State of Affairs and Current Progress

Broadband Electro-Magnetics (BEM): Brief Technical Description

- A BEM probe consists of two electromagnetically coupled coils (exciter and detector)
- The exciter coil is excited by a voltage pulse; Eddy currents are induced in the pipe
- The detector coil captures the resulting magnetic field
- This field contains information about the geometry and electromagnetic properties of the pipe





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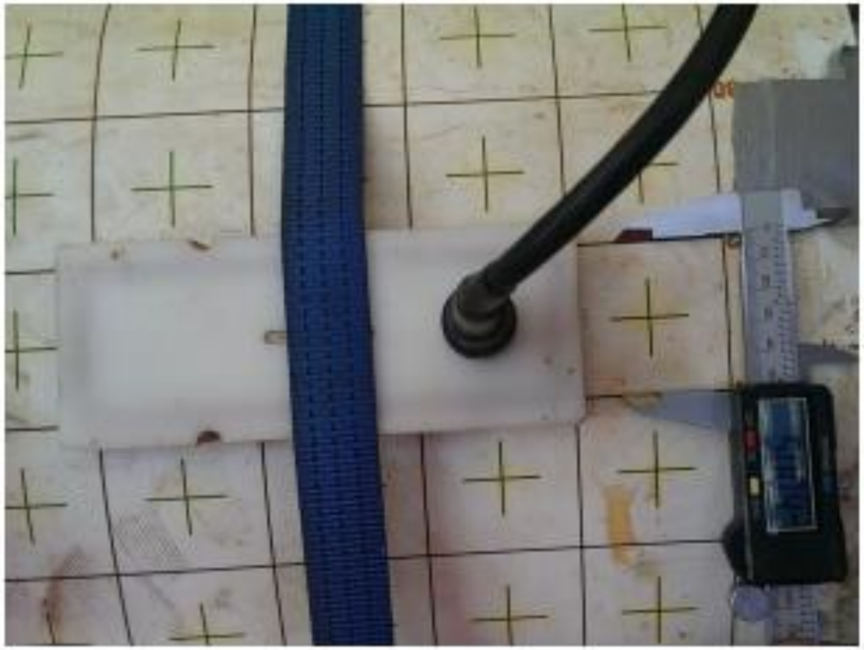
Broadband Electro-Magnetics (BEM): Brief Technical Description (cont.)

- The BEM coils need to be sufficiently large to energise the material in order to detect thickness of Critical Mains
- This is not a point measurement, rather a domain measurement
- Eddy currents detected belong to the energised **volume** of material beneath the sensor, it is a measure of **averages**
- Regular grid used to place sensor



Summary Current State of Affairs

1. UTS has delivered preliminary software for enhanced estimation of thickness from BEM data from their Single Sensor Antenna design
   - Readily available for use by Technology Provider
   - Added estimate of uncertainty
   - In accordance with desired project outcomes

2. Software performs estimation of thickness on-the-spot
   - 16 ms per measurement, including obtaining measurements from HSK Kit (~15 s)

3. A revised approach was proposed to produce more accurate estimates by introducing a novel feature extractable from raw BEM signals and by incorporating measured pipe material properties

4. Ph.D. study has been completed and the thesis has been submitted for examination

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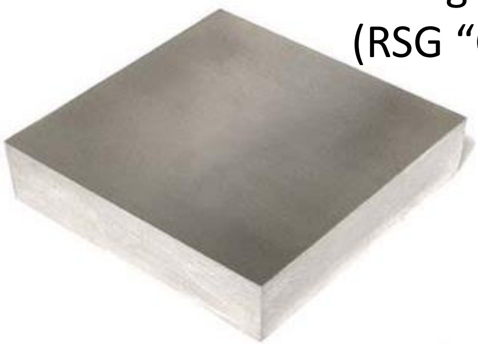
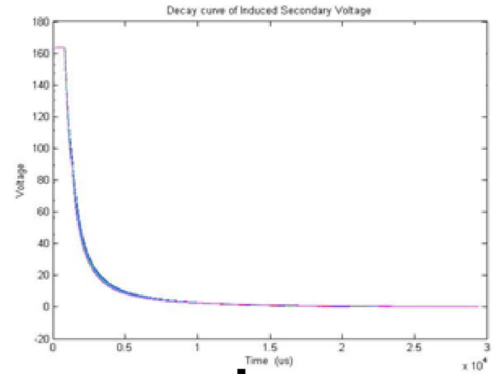
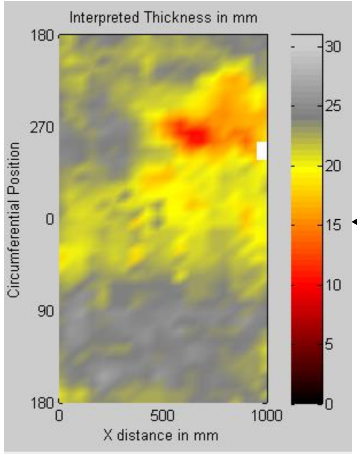
UTS Development: BEM Data Interpretation Model based on Calibration Blocks

Obtain generic calibration data
(RSG "Calibration Blocks")





Pipe profile



Data
Interpretation
Mode
(Analytical or
Probabilistic)

Testing data from pipe

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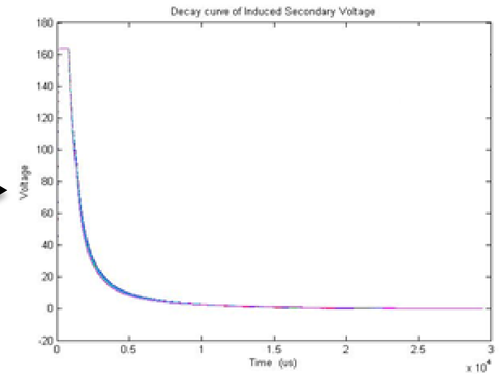
UTS Development: BEM Data Interpretation Model based on Numerical Simulations

To account for possible effects from variations in material properties

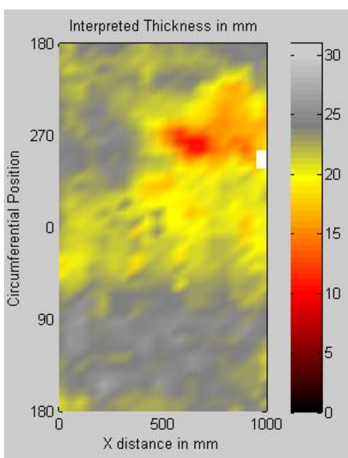
Obtain electromagnetic properties of pipe material

Numerical simulation of BEM tool = generate curves specific to pipe of interest



Data Interpretation Mode (Analytical or Probabilistic)

Pipe profile



Testing data from pipe

UTS Approach for Pipe Wall Thickness Estimation Approach

1. Pipe wall thickness (d) is estimated using a feature (β) extracted from the raw BEM signal and the feature relates to thickness through a function which can be described as

   $$d = f(\mu, \sigma, \beta)$$

   Where μ and σ are magnetic permeability and electrical conductivity of the pipe

2. Electrical and magnetic properties of pipe materials are therefore required as inputs for thickness to be inferred

3. These properties are unique to materials (i.e. gray cast iron, ductile cast iron or mild steel) and may vary depending on the vintage of a pipe, casting process, material composition and previous electromagnetic activity a pipe has been subjected to

4. As a result, measuring electrical and magnetic properties is important for accurate modeling of the BEM sensor, and producing accurate thickness estimates

Latest Progress

1. Trial 6 has been completed for further analysis, validation with GT yet to be completed, RSG report received

2. Driving towards extracting electrical and magnetic properties of pipe materials enable more accurate numerical simulations and data interpretation, and assess its influence in predictions:
   - Magnetic properties of 5 pipe segments and electrical properties of one pipe segment have been measured (PPMS equipment at Univ of Wollongong)
   - Further measurements are being performed from available samples and additional samples will be sent as necessary

3. Alongside Trial 6, RSG tested their newly developed multi-sensor antenna on the same pipes

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Ongoing Work: RSG Multi-Sensor Antenna

- Preliminary tests completed on UTS calibration blocks in June 2015, in situ measurements on pipes performed alongside Trial 6 in August 2015

- UTS is discussing on engagement for advancements in data interpretation and validation of the sensor

- RSG is planning on a second scan on Trial 6 pipes

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Ongoing Work: Material Properties

- Magnetic properties of 6 pipe sections have so far been measured with PPMS (4 from test bed, 1 ductile iron from Trial 4, 1 steel from Perth)
- More measurements are being performed on different pipe sections as required (i.e. Sydney water Φ550 mm, Perth cast iron trial)
- Electrical properties of one pipe section has been measured (from Test bed)
- Electrical properties of the remaining sections are being performed

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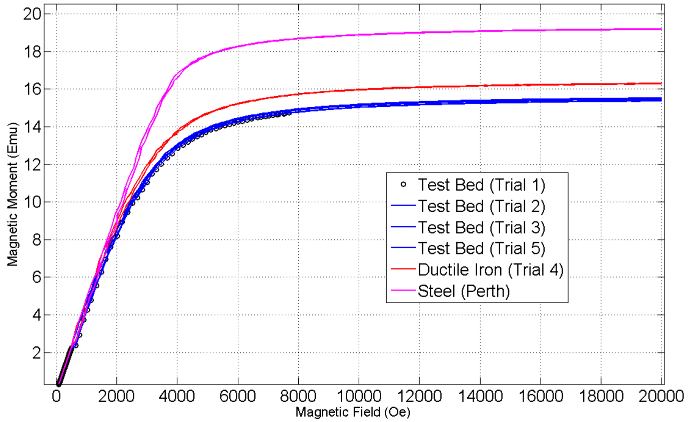
Latest Findings: Magnetic Properties

- Variation of Magnetic properties on the test bed across trials (Trial 1, 2, 3 and 4) is less than 1%.
- Significant variation across different materials
  - ~ 6% difference for ductile iron (Sydney Water) when compared with test bed
  - ~25% difference for steel (Perth) when compared with test bed
- This suggests that magnetic properties are fairly invariant for a long pipeline consisting of pipe sections with similar vintage
  - convenient for modeling -> performing few measurements of magnetic properties will be sufficient



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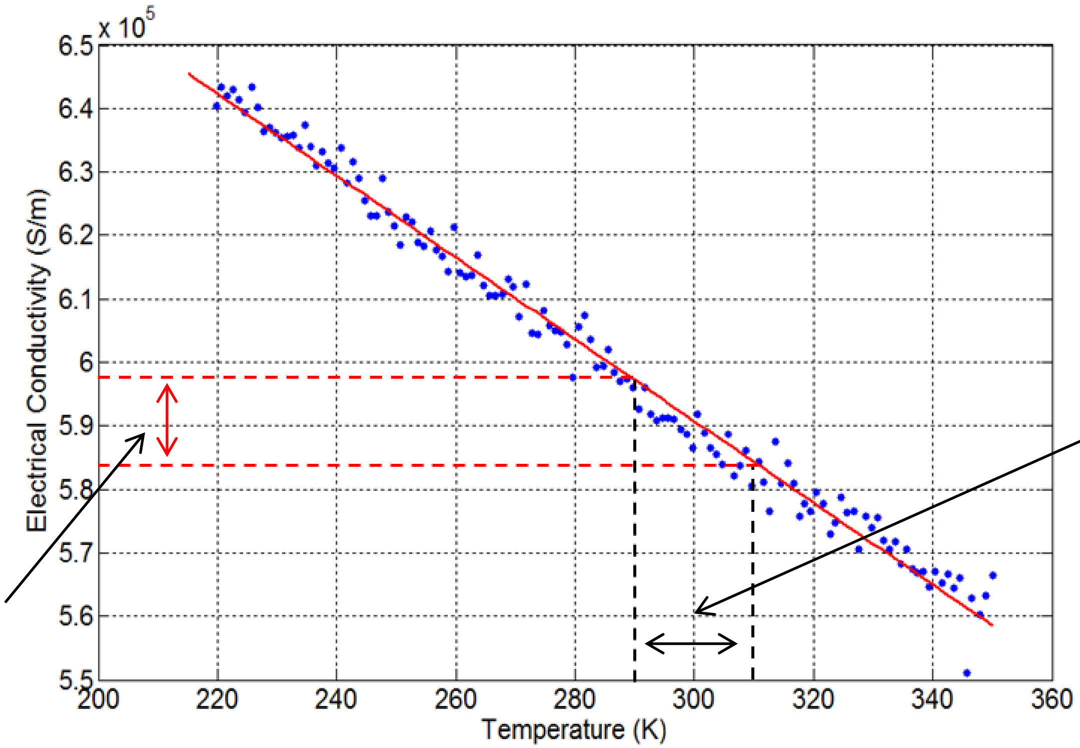
Latest Findings: Electrical Properties

- Quantified only on one pipe section (Test Bed: Trial 5 Anomaly 1)
- Temperature-dependence prevalent, but considerably insignificant (i.e. about 1% variation for 10 degrees of temperature difference in Celsius)
- Measurements on more samples are being performed



Corresponding variation in conductivity

A 20 degree ambient temperature variation usually existent in Australia

Objectives of Quantifying Material Properties

- Recall that pipe wall thickness (d) relates to a BEM signal feature (β) through a function in the form of

$$d = f(\mu, \sigma, \beta)$$

- The quantified variation of material properties can be incorporated in simulating the BEM sensor's behavior

- That will enable quantification of the variation in BEM signals caused due to the variation of material properties

- The variation in signals can be translated to uncertainty of the estimated thickness, a further indication of the level of confidence that can be placed on a estimate

BEM: Current Progress and Future Goals

Goal	Status
Developing a preliminary BEM data interpretation software package usable to RSG	Completed Beta version delivered to RSG
Developing more advance GP models using more discriminative features	Completed
Developing analytical model to infer pipe wall thickness (for Grey Cast Iron, Ductile Iron and Mild Steel), tested on calibration data from RSG	Completed
Numerically simulating the BEM Antenna interacting with pipe materials by using realistic material properties	Completed
RSG interpretation vs. Ground truth comparison (Trial 2,3,4,5,6)	Completed, Trial 6 in progress
UTS interpretations vs. Ground truth comparison (Trial 2,3,4,5,6 & Perth)	Completed, Trial 6 in progress
Studying the effect of lift-off on the BEM antenna to evaluate the capability of scanning through cement lining	Completed
Developing BEM laboratory setup	Completed
Ph.D. study and thesis submission	Completed
Capturing variations in material properties and developing an advanced "Simulation + GP" based model to infer pipe wall thickness	In progress
Liaison with RSG to validate and advance the multi single antennae sensor for field deployment	In progress

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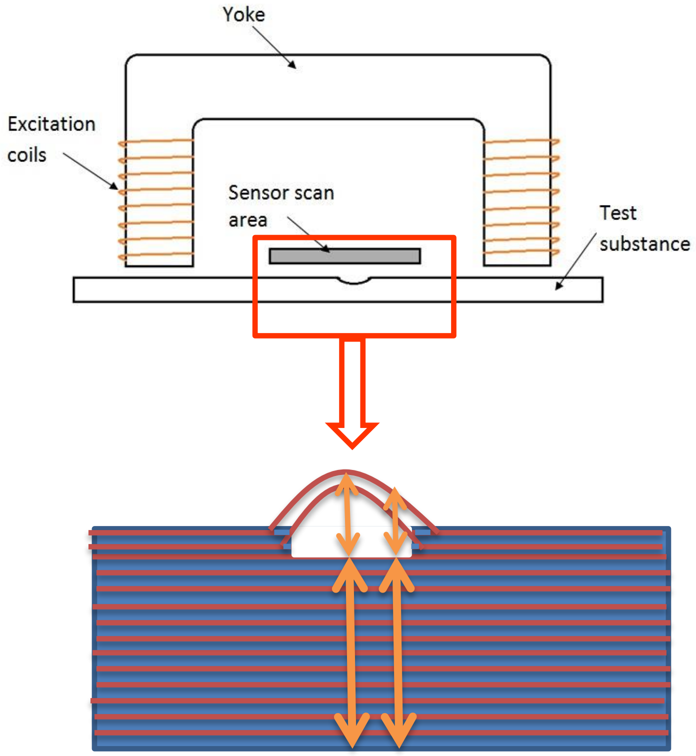
MFL (AIA): State of Affairs and Current Progress

Magnetic Flux Leakage (MFL): Brief Technical Description

- Saturate the pipe material with a strong magnetic field
- Flux tends to leak out with cracks/defects
- Magnitude of the leakage flux is used to estimate the remaining wall thickness at defects
- Therefore, the state of the art MFL technologies provide measles plots (not 3 dimensional reconstruction)



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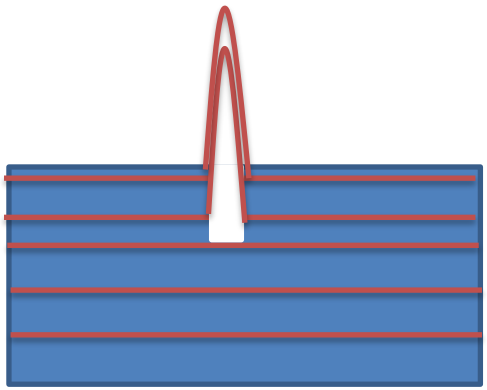
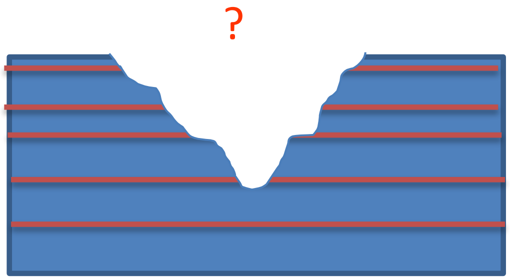
Magnetic Flux Leakage (MFL): Challenges

- MFL signal is affected by (not exhaustive)
  - Variations in the air gap - needs to be kept constant
  - Variations in the pipe materials – inhomogeneous
  - Variations in pipe thickness - in manufacturing
  - Shape of the defects – Cylindrical, conical etc
  - Distribution of the defects



- Combination of above and possibly others can contribute to prediction errors



Summary Current State of Affairs

1. Software Module (deliverable)

   – A beta version of the UTS data interpreter '*MFL_Data_Interpreter_v1.exe*' was delivered to AIA/AESL on 17/03/2014 and received feedback on 03/06/2014

   – The software was improved to interpret data from different CI pipe thicknesses given the nominal thickness

   – Two personnel, Dr. Bob Fisher and Ewan McDonald from AIA/AESL visited UTS and discussed the developments on 25th of November 2014

   – Identifying the importance of UTS work, Ewan McDonald spent a week (From 1st December 2014 to 5th of December 2014) at UTS to understand the framework developed by UTS which is the core of the software package

   – Ewan McDonald compiled a report to AESL along with the software documentation done by UTS

   – A comprehensive document ('AIAResultsEvaluation_20141107.pdf') illustrating the accuracies of the AIA/AESL predictions (RWT) and UTS prediction (RWT) on Trial inspections was sent to AIA/AESL on 07/11/2014

   – UTS received AESL feedback on 21/04/2015

Summary Current State of Affairs

2. Overall AIA/AESL Interpretations: Error Analysis

   – In order to accommodate misalignments between laser measured RWT and AIA raw data scans (thus reported by AIA/AESL and UTS RWT locations), a search window of 10cm x 10cm in the laser measured RWT is used

   – Results are plotted against the matched defects in the laser measured RWT. Average Root mean square (RMS) error is 12.72mm for AIA reported RWT, and 4.59mm for UTS predicted RWT

Latest Progress on MFL

1. According to Bob Fisher "AESL are currently exploring the development of UTS models for all pipe diameters and materials" in collaboration with Newcastle University, UK

2. Buddhi Wijerathna completed his PhD thesis on "Magnetic Flux Leakage Based Advanced Condition Assessment for Aged Cast Iron Pipes" – currently under review

3. Analytical Model-Aided Optimisation for Ellipsoidal Defect Approximation

4. Reconstruction of Dense 2.5-D Thickness Maps using MFL Measurements

Analytical Model-Aided Optimisation for Ellipsoidal Defect Approximation

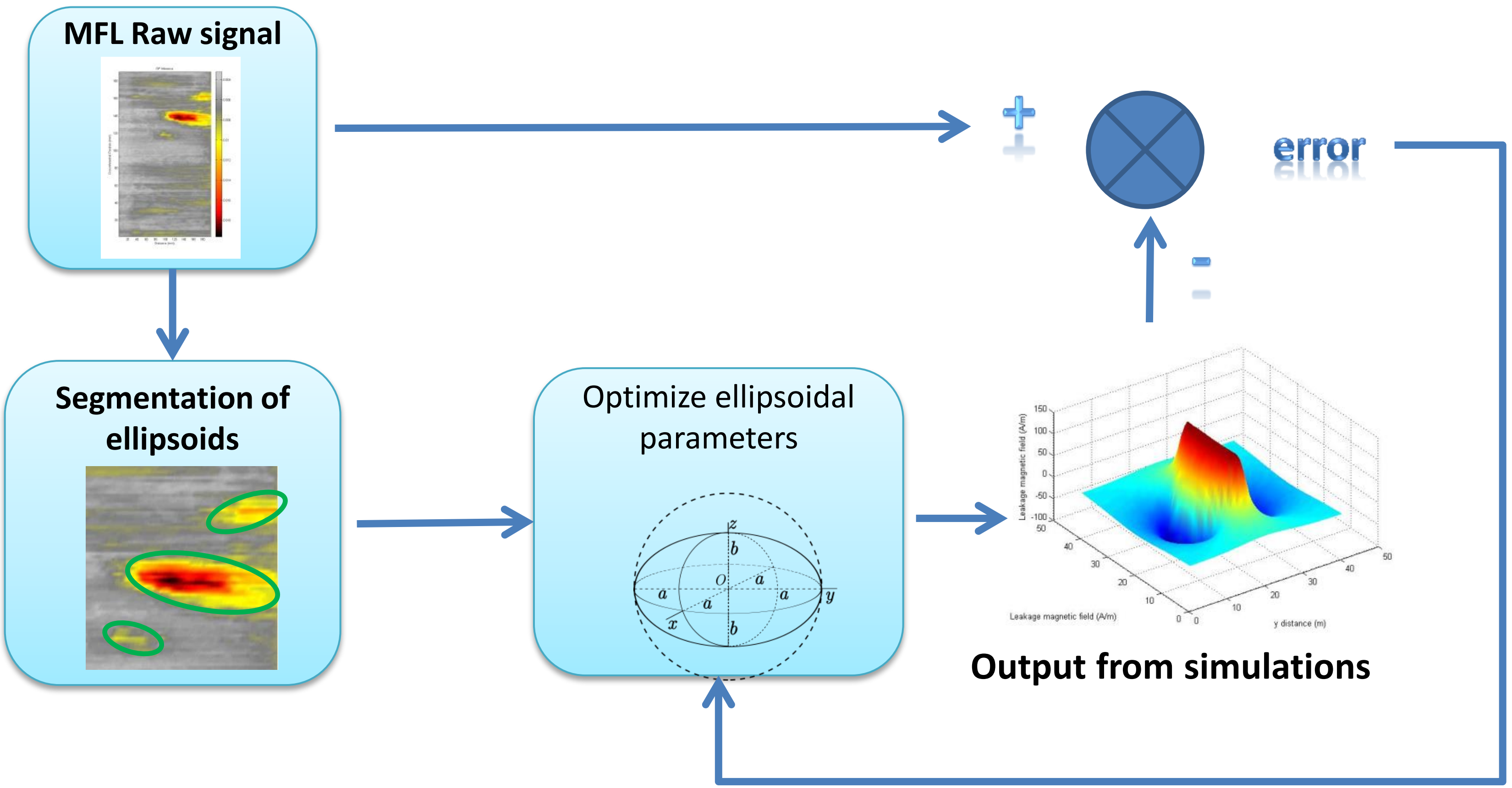
1. With the findings from Activity 1, it appears ellipsoidal-type defects are more prone to cause pipe failure than single pitting as currently reported

2. Investigations have been carried out to approximate ellipsoidal defects using raw MFL data

   - An optimization method has been proposed

   - Extensive simulations as well as real measurements from Trial 6 used to validate the method

Iterative Ellipsoidal Approximation Framework



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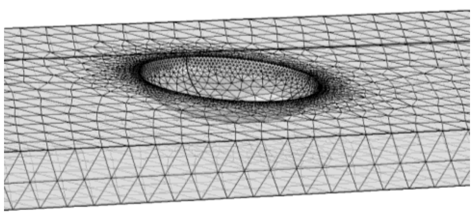
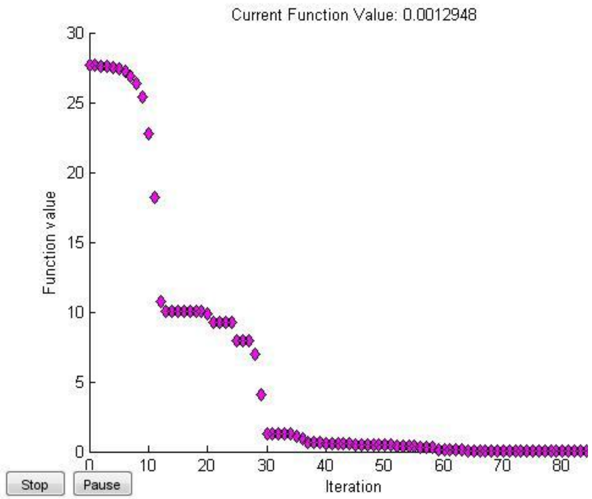
Proof of Concept Using Simulated Data

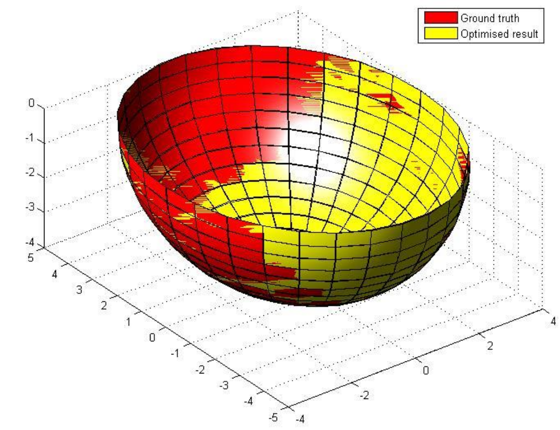
- A simple ideal ellipsoid defect was simulated using FEA (Comsol Multi-Physics)
- Dipole model based analytical model was used to optimise the ellipsoidal parameters
- Converges with ±0.1mm



FEA based ellipsoid simulation



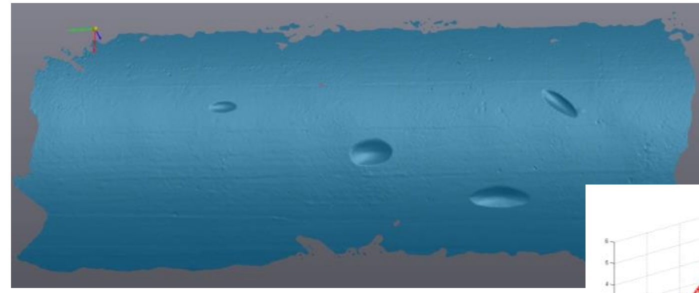
Convergence of the optimization



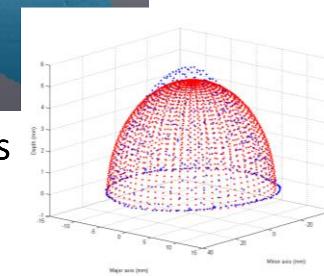
GT vs optimized result

Validation Using Machined Ellipsoidal Defects - Trial 6

Machined ellipsoidal defects



Laser scanned ellipsoidal defects



Machined Ellipoid	Axial major elliptic diameter (a)		Radial minor elliptic diameter (b)		Depth of the ellipsoid (c)	
	Laser based fit	UTS prediction	Laser based fit	UTS prediction	Laser based fit	UTS prediction
1	23.31mm	25.23mm	13.8mm	12.3mm	3.09mm	2.3mm
2	34.2mm	34.6mm	22.5mm	22.3mm	7.68mm	7.1mm
3	49.7mm	51.6mm	20.3mm	19.5mm	6.5mm	6.1mm
4	35.09mm	41.12mm	12.14mm	10.05	5.1mm	3.73mm

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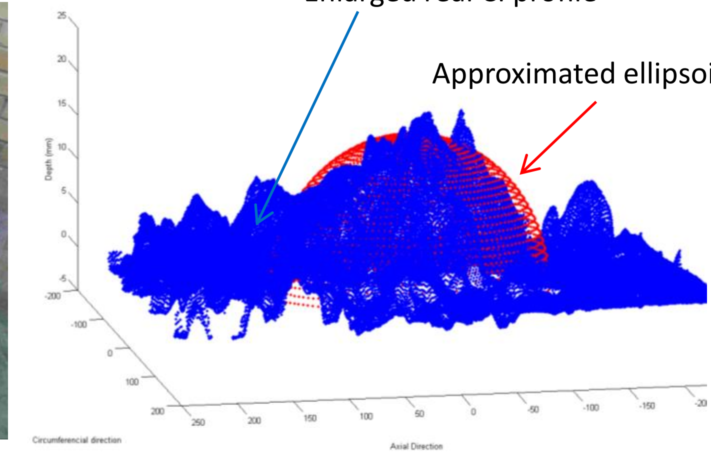
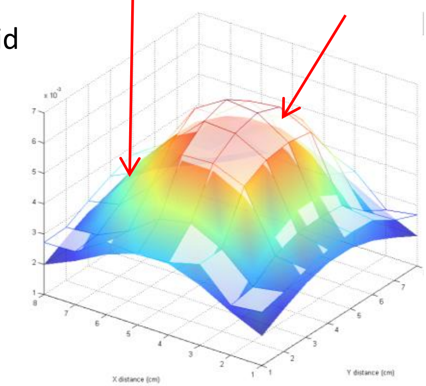
Framework Evaluation on Real Test-bed CI Pipes



Enlarged GT profile
and approximated ellipsoid



Optimized leakage field

	Axial major elliptic diameter(a)	Radial minor elliptic diameter (b)	Depth of ellipsoidal defect (c)
Laser based fit	125.1mm	64.4mm	18.14mm
Framework predicted	119.6mm	57.7mm	21.3mm

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Reconstruction of Dense 2.5D Thickness Maps using MFL Measurements

- Commercial MFL (AESL) finds pitting
- Driven by Activity 1 findings, UTS research has revealed it looks reasonable large ellipsoidal defects can be isolated from raw data
- Q: can the FULL dense map for a single exposed section be recovered?

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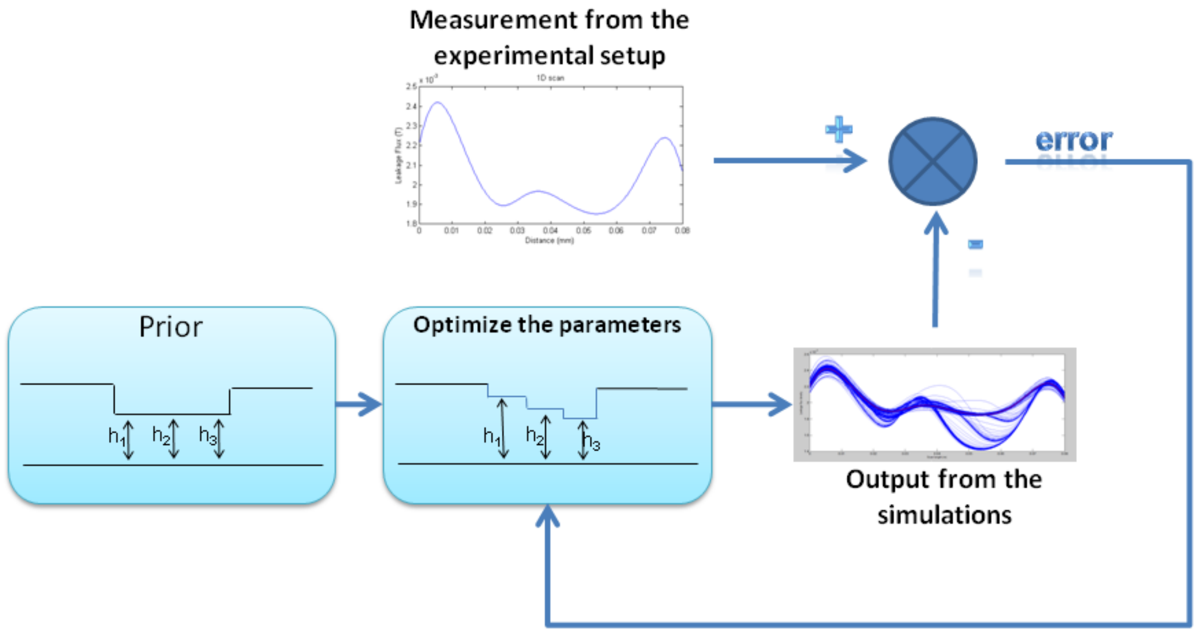
Reconstruction of Dense 2.5D Thickness Maps using MFL Measurements (cont)

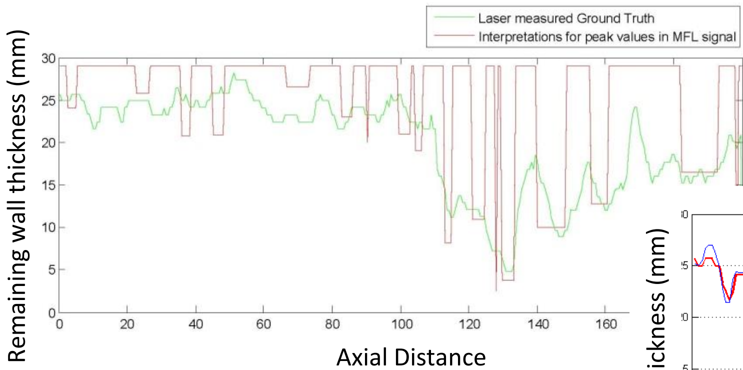
- Analysis of MFL raw measurement signals indicate that it contains information about the full thickness profile
- Ill-posed nature of MFL inverse problem makes it challenging to extract this information if addressed as a concatenation of independent MFL ‘points’ (as initially undertaken on this research)
- Quasi-Newton least squares iterative optimisation framework has been developed to reveal thickness profiles
- 2.5D thickness profiles can be reconstructed using the framework

Framework for Reconstruction of Dense 2.5D Thickness Maps

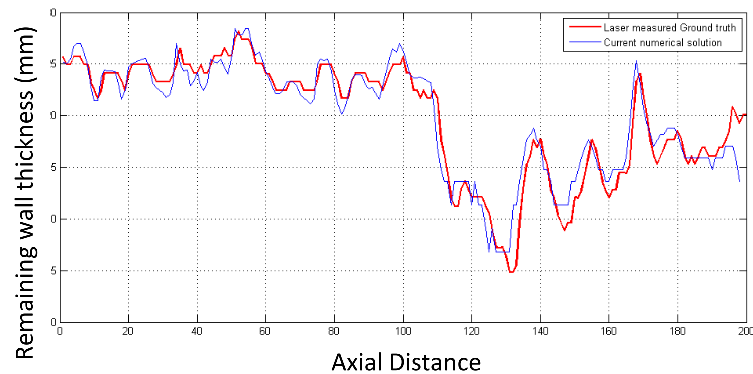


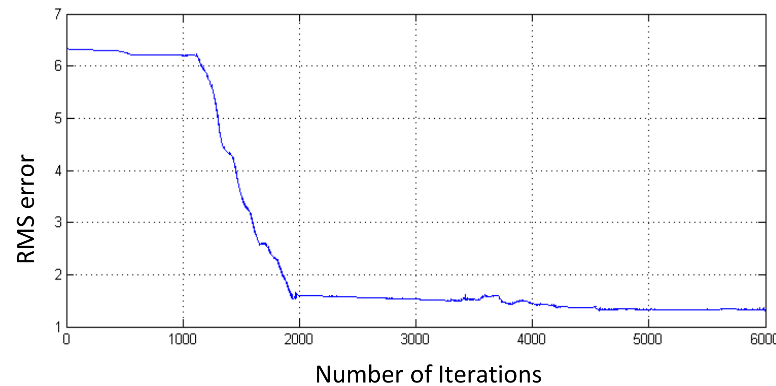
- It complements current GP proposition for higher accuracy
- The initial results are convincing however it is computationally intensive

Reconstruction of Dense 2.5D Thickness Maps - Results



Coarse to fine iterative approach using GP – peak based result as the initial seed





RMS error variation with number of iterations

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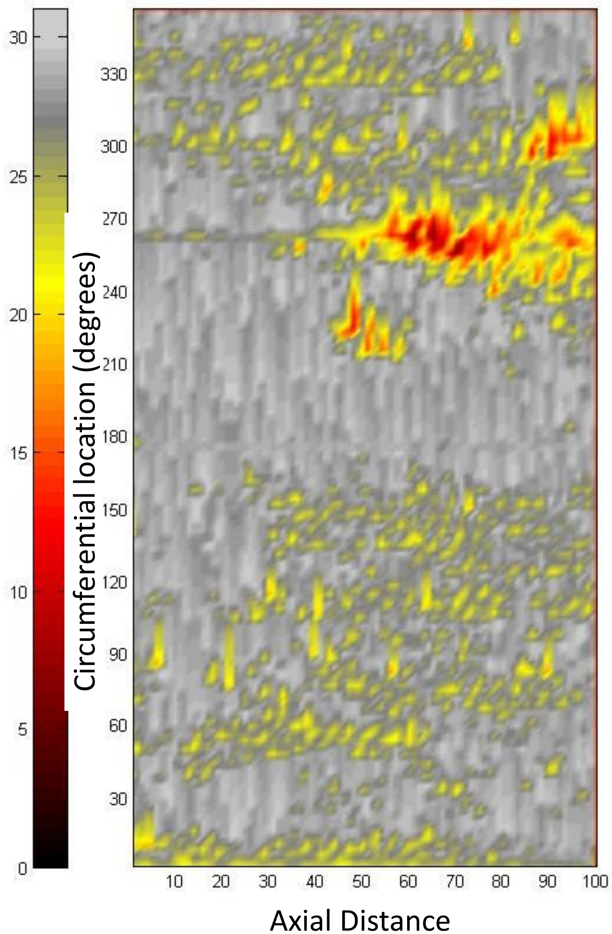
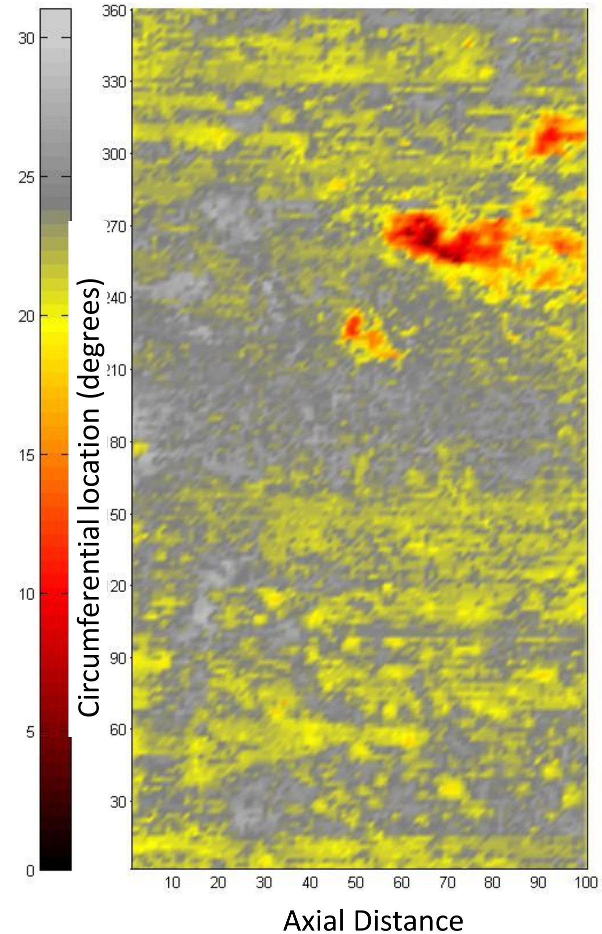
Iterative Coarse to Fine Approach - Results

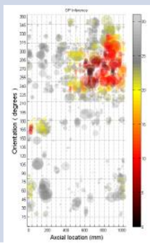
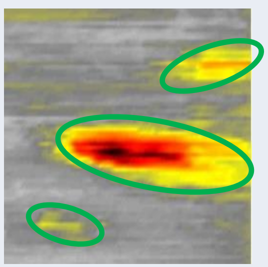
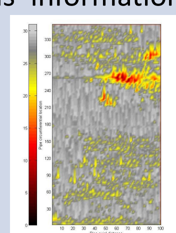


2.5D Optimized solution



Ground Truth

Current UTS Interpretations from MFL Signals

	Pros	Cons
Measles plot • Industry partner produces measles plots 	• Fast generation of the plot (~ 5 minutes) • Can identify defect sizes as individual pits	• Defects approximated to cylindrical defects • Cylinders overlap to each other • Needs pre-trained models
Ellipsoidal approximation • As per feedback from Activity 1 	• Can be used for stress analysis purposes • Fast computation (~7 minutes per ellipsoid)	• Does not produce a detailed dense representation of the pipe section remaining wall thickness
2.5D thickness map • MFL signal has information to produce thickness map 	• High resolution 2.5D representation of the remaining wall thickness	• Computationally very expensive (~10 days of automated data processing)

MFL: Current Achievements

Goal	Status
Generation of 3D defect profiles using machine learning	Completed (punished at SIPE conference)
Design and prototype of a MFL lab setup	Completed (capacity to further improvements)
Development of a realistic simulation for UTS MFL lab setup	Completed
MFL Software interpretation tool development	Delivered Beta version delivered (to AIA) and on-going improvements for generalization
Development of a realistic simulation model for the output of AESL tool	Completed (based on limited available feedback and contrasted data)
AIA /UTS predictions Vs Ground truth analysis	Completed (Report sent to AIA)
Analytical Model-Aided Optimisation for Ellipsoidal Defect Approximation	Completed (needs further testing)
Reconstruction of Dense 2.5-D Thickness Maps using MFL Measurements	Completed (needs further testing)
Buddhi Wijerathna PhD thesis on “Magnetic Flux Leakage Based Advanced Condition Assessment for Aged Cast Iron Pipes”	Completed (submitted, under review)

RFT (Russell NDT/PICA): State of Affairs and Current Progress

Outline

- Slides from TAC June 2015 Reviewed by Russell NDE/PICA Corp

- Current progress on RFT Analysis
  - Discussions back and forth with Russell NDE/PICA Corp
  - Recent developments

Feedback from (last) TAC June 2015 after Comments and Review by Russell NDE/PICA Corp.

To be presented during TAC for discussion

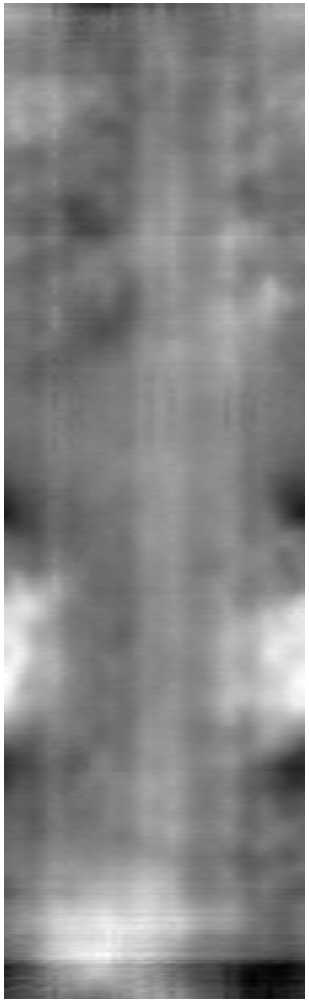
Current Progress on RFT analysis

How Best to Characterise Defects on RFT signals?

- Aim: develop a method to recover <u>shape</u> and <u>size</u> of large defects from raw RFT signals
  - Driven by interest from technology provider and Activity 1 findings
- Shape (extension of the defect in axial and circumferential directions)
  - Use techniques similar to image segmentation in computer vision
  - Supervised learning to automatically segment the shape of large defects
    - Manual segmentation needed learn and validate segmentation models
- Size (remaining wall thickness)
  - Phase-shift of RFT signal appears ~ linear wrt thickness:
    - A methodology to find this relationship needs to be developed
  - This relationship between RFT signal and thickness to size defects will then be learned:
    - Signal features for this will be evaluated in a supervised learning framework

Defect Characterisation - Manual Segmentation

- Machine learning approach for defect sizing and characterisation
- The first step is to segment defects in the RFT signal to analyse them independently
- The reference is based on manual segmentation (right image) using the information contains in the post processed phase-shift (left image)

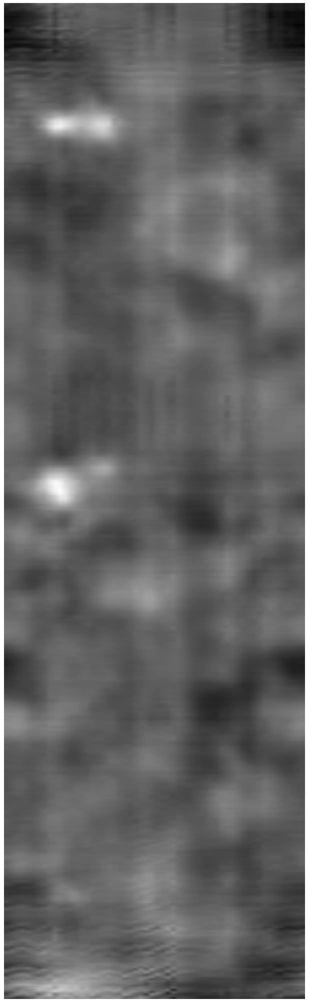


Phase-shift

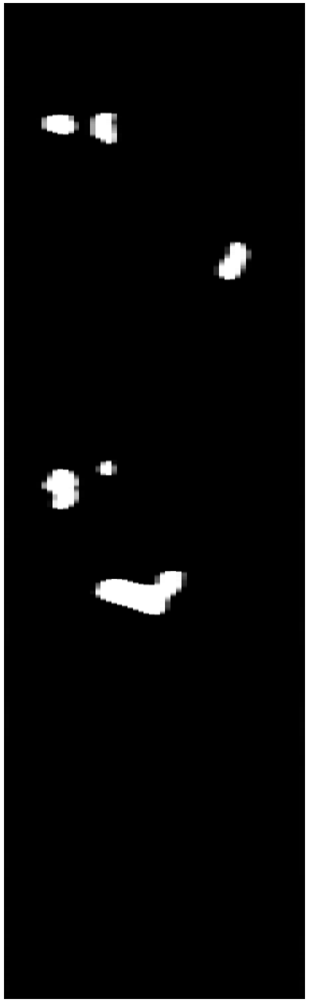
Manual segmentation

Defect Characterisation - Manual Segmentation (cont)

- Machine learning approach for defect sizing and characterisation
- The first step is to segment defects in the RFT signal to analyse them independently
- The reference is based on manual segmentation (right image) using the information contains in the post processed phase-shift (left image)



Phase-shift



Manual segmentation

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Defect Characterisation – Feature Extraction

- Features are extracted on both the phase-shift and amplitude
- The information will be defined in a vector containing :
  - Raw values
  - Defect field
  - Background field
  - Amplitude and phase-shift
- The values of the signal at 2.3m upstream and downstream will also be used
  - The upstream signal contains information related to wall thickness
  - The downstream signal contains information related to the noise in the signal

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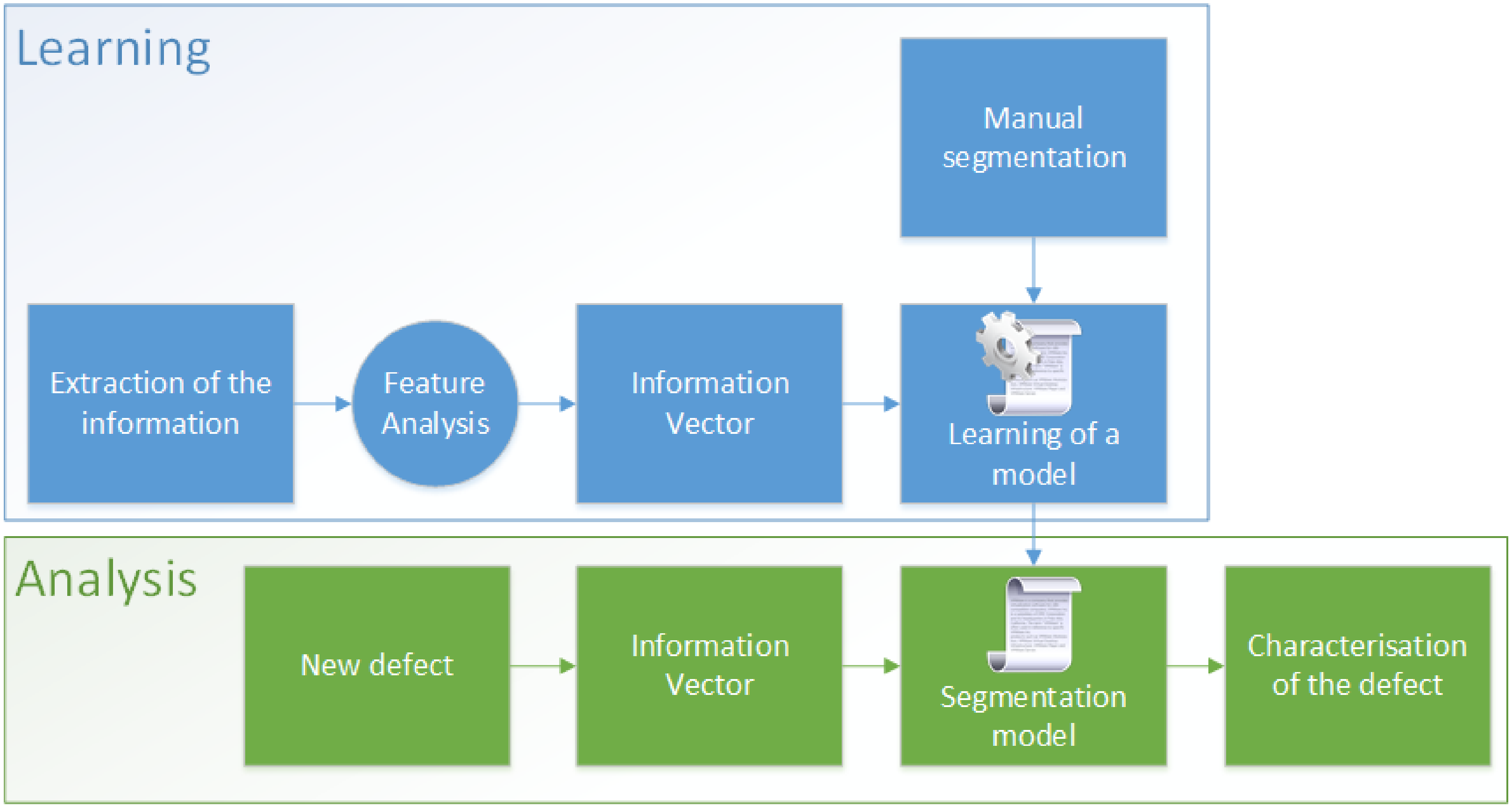
Defect Characterisation – Shape Segmentation

- In order to select relevant features, and algorithm such as Principal Component Analysis (PCA) can be used to avoid redundancy in the feature vector

- Training of a classifier on a two class problem (equivalent to segmentation)
  - Classic supervised learning (GP, Bayesian, …)
  - Deep learning (Neural networks)

- We will compare different methods to select the most appropriate to fully characterise shape and size of defects in raw RFT signal

Defect Characterisation – Supervised Learning



RFT : Current Progress and Future Goals

Goal	Status
Numerical simulation of the RFT tool interacting with pipe materials	Completed
Pre processing pipeline implemented	Completed [ACRA Paper - Published]
Implement a defect detection algorithm for significant defect in RFT data	Completed
RFT interpretation vs. Ground truth comparison (Trial 2,3,5)	Completed
RFT interpretation vs. Ground truth comparison (Trial 6)	In-progress
Implementation of a shape detection algorithm for defect characterisation in raw RFT data	In-progress
Feature analysis on the RFT raw signal to characterise defects (in terms of shape and size)	In-progress
Further analysis on data normalisation for thickness interpretation (already with the engagement of Russell NDE)	In-progress

What Have We Learned About BEM in CI

1. A BEM signal does **NOT REPRESENT** a point measurement of wall thickness, it measures **AVERAGE VOLUME** of material under the sensor antennae
   - A single BEM measurement represents an area of 50mm x 50mm
2. BEM **CAN NOT** detect pitting
3. In CI pipes, RSG interpretations seems to **relate well** to actual volumes of pipe thickness
4. Pipe ferromagnetic properties (e.g. conductivity, permeability) affect results
   - Good estimations of these properties produce best interpretations of remaining wall thickness
   - If not considered, there exists an offset between interpreted and real wall thicknesses
5. Multiple **receiver** antennae (e.g. 6 way antennae) is less suitable to produce results of similar sensitivity to single **receiver** antenna sensor, RSG researching on a new multiple **sensor** antenna
6. Preliminary analysis indicate **suitability** for stress analysis, if **coarse**

What Have We Learned About MFL in CI

1. MFL signals can approximately **REPRESENT** a point measurement: it measures the material under the tool

2. MFL **CAN** detect pitting

3. AIA Interpretations are **idealised shape defects**

4. AIA reports a plot locating 10 worst (depth) defects per 1m axial inspections

5. A nominal value (e.g. utility supplied info, average ultrasound spot measurements) is needed as a reference to measure leakage/defects

6. In CI pipes, AIA interpretation does **NOT SEEM** to relate well to actual pipe profiles of wall thickness in relation to defect depth or location

7. MFL data can be interpreted in **ellipsoidal large defect** form to assist the SCF equations for **stress analysis**, and/or for gaining more pipe detail from sparse data (see Activity 4a)

What Have We Learned About RFT in CI

1. An RFT signal does **NOT REPRESENT** a point measurement of wall thickness, it measures volume of material under the receiver coil antennae
   - The location of defects is given according to their centre with an accuracy of 2mm along the axial direction, and 82mm along the circumference

2. RFT can **not** detect high-resolution pitting (it depends on the size of the receiver coil, which remains unknown)

3. Russell NDE's RFT implementation is an in-line Inspection pig with an array of receiver antennae around the circumference of the pipe

4. In CI pipes, Russell's interpretations seems to **relate** to actual **average** volumes of pipe thickness

5. Pipe ferromagnetic properties (e.g. conductivity, permeability) induce a source of noise in both components of the signal (amplitude and phase shift)

6. Current provider analysis (pitting defect and average RWT) appears unsuitable for stress analysis. Like MFL, **larger ellipsoida**l shape defects from raw data appears **promising.** Moreover, sparse defects can **contribute** to information gain in a **fusion** step (see Activity 4a)

What Have We Learned About Acoustic PWA in CI

1. Acoustic PWA detects anomalies on pipe wall through acoustic wave propagation

2. Pure's Acoustic PWA is an In-line Inspection technique

3. Measurements represent pressure waves which could be related to **AVERAGE** pipe thickness. This is not straightforward

4. Pure's Acoustic PWA appears to **lack** the **sensitivity** for detecting pipe wall losses/defects in **large metallic pipes**

5. Preliminary results appear more promising in non-metallic AC pipes

6. Sahara PWA remains a technique under development

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What Have We Learned So Far about CA in CI

1. All techniques have got shortcomings in being able to provide an accurate picture of pipe wall thickness

2. From a qualitative point of view of CA, all techniques provide some information relevant to the CA processes carried out by utilities – as it is being done today

3. As per guidance from Activity 1, from a quantitative point of view CA interpretations provided in current inspection reports by most technologies (i.e. MFL, RFT, Acoustics) might not be fit for the purposes of stress analysis and failure prediction. However, in most cases the raw data is being proven to be able to do so

4. Summarising the perceived limitations and reported accuracies of the various techniques pose significant challenges. Given the sensing principles of each technique, establishing these for the purpose of failure analysis in conjunction with Activity 1 and 3 constitutes the final phase of this project