Advanced Condition Assessment & Pipe Failure Prediction Project

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Progress on Activity 2 - Multiple Defect Interpretation for MFL Technology: Gaussian Processes Approach

Overview

The Magnetic Flux Leakage (MFL) concept has been used in non-destructive testing for more than three decades. However, due to the presence of large parametric variations and difficulty in accurate physical modelling, data driven machine learning techniques have been in the forefront of research focus in recent years. Most of the work is still limited to MFL based interpretation of isolated defects. As an initial study, here we propose to interpret two defects scenarios based on magnetic flux leakage. The approach is validated through simulations and experiments.

Background

Magnetic Flux Leakage technology has been used in non-destructive evaluation (NDE) for more than three decades. In the MFL inspection process, a sample of a ferromagnetic material is magnetized using a strong magnetic field and in the presence of defects or anomalies, a magnetic flux "leak" can be detected. Suitable sensors are employed to scan this leakage field on which different signal processing techniques are applied for detection and sizing. The use of advanced signal processing and analysis technologies may result in more accurate modelling and prediction. In particular, machine learning algorithms appear well-suited for robust modelling of MFL signals. Two main frameworks are generally employed to model MFL signals. The traditional approach requires knowledge of precise calibration samples to generate MFL signals which are compared with fresh measurements to infer the most likely defect profile. The inverse approach fits a model that can be used to predict the defect configuration from the MFL signals.

This study is focused on the inverse model of MFL signals by using state of the art machine learning techniques in order to detect and size multiple defects. Supervised learning in the form of regression is an important constituent of machine learning for inferring a function from a "labelled" data set, i.e., measurements associated with their ground truth. Traditionally parametric models have been used for this purpose. These models have a possible advantage in ease of interpretability, however for complex data sets simple parametric models may lack expressive power, and their more complex counterparts may not be easy to work with in practice. The advent of non-parametric processes, such as Gaussian Processes (GP), has opened up the possibility of flexible models which are practical to work with. Gaussian Process models can conveniently be used to formulate a Bayesian framework for nonlinear regression. In this work, we use GP models to solve the inverse MFL model problem.

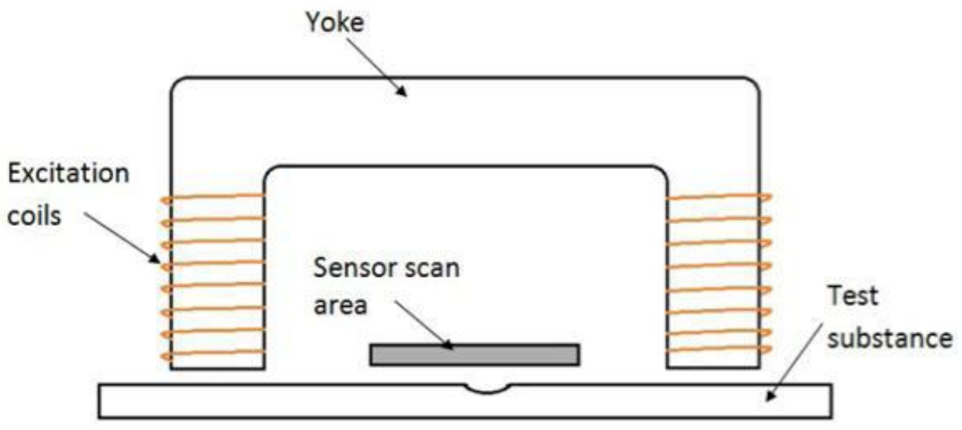


Figure 1 Illustration of a generic MFL device

Approach

The approach consists of learning the inverse model to characterise the geometry of multiple defects, i.e., depth, width, separation and number of defects in a metal piece using MFL measurements as inputs.
We make use of simulated and real data with their corresponding defect dimensions to build these models in a supervised learning manner. The steps in this process are:

Step 1
Carry out a large number of simulations by varying depths, widths and separations of two defects while capturing the axial component of the associated leakage magnetic fields.

Step 2
Reduce the dimensionality of the data by extracting features of the signals.

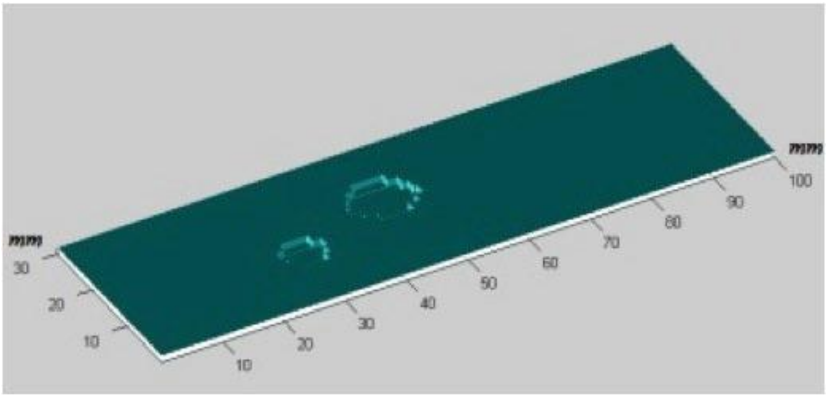
Step 3
Train separate GP models for depth, width and separation of two defects.

Step 4
Infer the defect parameters of new MFL data based on the learned GP models.

Preliminary Results

An experimental set up is used to measure MFL signals on a soft iron plate shown in Figure 2 (a). All three models have been utilized and the results were combined together to reconstruct the defect geometry as shown in Figure 2 (b). Table 1 shows the numerical comparison of the actual and predicted defect parameters. However, it is to be noted that errors are not only due to the proposed GP approach, but also due to various other experimental factors such as the errors in the linear slider which was used to slide the sensor along with the mechanical arrangement (which has 0.5mm error margin).

(a) Soft iron plate used in the experiment



(b) Reconstructed defect geometry
Figure 2 Comparison of the defect depth profile

	Left defect		Right defect	
	Real	Reconstructed	Real	Reconstructed
Diameter (max. width)	10 mm	11.3 mm	20 mm	19.1 mm
Average	2.5 mm	2.375 mm	2.55 mm	2.325 mm
Defect separation	25 mm	26.1 mm		

Table 1 Numerical comparison of real and predicted parameters of defects

Summary

In this preliminary study, we have proposed an approach to solve the inverse model problem of defect detection and sizing for MFL signals by employing Gaussian process regression. A finite element analysis based simulation model was exploited to generate a sufficient amount of data needed for the training process of the proposed supervised learning algorithm. The learned GP model was used to infer multiple defect dimensions, which were in turn compared qualitatively and quantitatively with the ground truth showing correct agreement.

The advantage of the method presented here is that the obtained model is nonparametric with only a few parameters being manually tuned. Moreover, each prediction comes along with the uncertainty values associated with it; the more data used for the training process, the tighter the uncertainty margins of the prediction. This work is published in SPIE Smart Structures/NDE conference in March 2013.

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.

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