**Sensor modelling for BEM Technology: Gaussian Processes Approach**

**Overview**
Broadband Electro-Magnetic (BEM) concepts have been deployed in non-destructive testing by Rock Solid Group (RSG) for almost two decades. Due to the presence of large parametric variations and difficulty in accurate physical modelling of the sensor to pipe interaction, data driven machine learning techniques have been proposed and are being investigated. The approach is validated through simulations and experiments.

**Background**
Eddy current non-destructive testing is one of the most conventional electro-magnetic methods utilized for the inspection of conductive materials. In particular a technique commonly known as Eddy-Current Broadband Electro-Magnetic (BEM) Testing, which is a sub-category of the Pulsed Eddy Current (PEC) testing method is the underlying technology employed by RSG.

In the BEM inspection process a ferromagnetic material is magnetized using pulsed eddy currents. This varying magnetic field causes an interaction between a magnetic field source and the test material resulting in induced eddy currents in the test piece. Once the magnetic field from the source subsides, detecting and monitoring changes in the eddy current flow in the test piece enables detection of remaining thickness.

The traditional approach to estimation of thickness of remaining material from BEM signals involves semi-supervised labelling of measurements obtained in-situ against calibration samples to infer the most likely remaining thickness. 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 BEM signals.

Supervised learning in the form of regression is an important constituent of machine learning for inferring a function from a “labelled” data set, e.g. 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 models, such as Gaussian Processes (GP) has opened 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 sensor model problem.

![Figure 1. 3D view of an exhumed pipe from Trial 2 (September 2012)]
Approach
The approach consists of learning a sensor model to characterise the remaining material thickness under the sensor using BEM measurements as inputs. We make use of data acquired from calibration samples of cast iron with their thickness (as seen in Figure 1) to build these models in a supervised learning manner.

Step 1: Carry out gathering of calibration plate data (varying thickness) capturing the voltage related to the decaying magnetic field from the sensor.

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

Step 3: Train GP model for thickness.

Step 4: Use the learned GP models to infer defect parameters from new BEM data.

Preliminary Results
Initial results with data obtained from inspection of a pipe segment from the Sydney Water test-bed can be seen in Figures 2 and 3.

Figure 2. Remaining wall thickness of an exhumed section of pipe (obtained with a 3D laser scanner at a test-bed site during trial 2. Pipe section currently at UTS)

Figure 3. Estimates of remaining wall thickness (a) results obtained using the GP sensor model, and (b results provided by RSG

Summary
In this preliminary study, we have proposed an approach to estimate the remaining wall thickness by employing Gaussian Process regression. A collection of decay curves from calibration blocks was exploited to generate the data needed for the training process of the proposed supervised learning algorithm. The learned GP model was used to infer remaining wall thickness which was 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 manually tuned. Moreover each prediction comes along with the uncertainty values associated with it; generally, the more data used in the training process, the tighter uncertainty margins in the prediction.

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