

Automatic Data Interpretation and Enhanced Localization for Inline Remote Field Eddy Current Tools

by

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Declaration of Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

Faculty of Engineering and Information Technology

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Doctor of Philosophy

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Most of the water pipelines laid in the 20th century, in Sydney, are made of ferromagnetic materials that corrode with time. Corrosion weakens the structure of the pipes and may eventually lead to catastrophic failures. Thus, regular inspection and maintenance of critical-pipes is needed which is both costly and challenging. Non-Destructive Evaluation (NDE) technologies, such as Remote-Field Eddy-Currents (RFEC), are a cost-effective option to assess the condition of pipes.

RFEC technology is based on the double-through wall phenomenon, which results in having different areas of the pipe's geometry being convoluted into the RFEC sensor measurements. Thus, the interpretation of the signal into thickness information is a challenging task. The technology is traditionally studied using Finite Element Analysis (FEA) for very simple geometries. Examples found in the literature tend to consider for instance perfect cylindrical pipes in the presence of square axisymmetric defects. In practice, these experiments do not translate well with the organic shapes generated by the corrosion, and these idealistic scenarios bypass the need for signal deconvolution. Furthermore, the behaviour of the tool in three-dimensional space is not well understood.

In this thesis, FEA simulations are performed on geometries obtained from real corroded pipes. Thus, the simulations are a reflection of a realistic RFEC inspection.

Based on FEA, data-driven algorithms have been designed to solve the direct and inverse problems for homogeneous materials and to solve the signal deconvolution for non-homogeneous materials (which requires an additional piecewise linear transformation to fully solve the inverse problem), in both, the two-dimensional axisymmetric scenario and the three-dimensional scenario. These algorithms have been tested on datasets obtained through simulations, as well as, field deployment of an inspection tool. Additionally, a localisation algorithm is proposed to align the RFEC data obtained from the field inspection with laser-scan measurements used as ground truth. Finally, a methodology for automating the data analysis for the extraction of defects present in RFEC data (in terms of localisation and 2D shape segmentation) has been developed and tested with real data. As a result, a framework is proposed to process raw RFEC data and ultimately extract the location and shape of defects which will, in turn, assist with pipe failure prevention.

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Acronyms & Abbreviations

2D	two-dimensional
3D	three-dimensional
B&S	Bell and Spigot
BEM	Broadband Electromagnetic
BPNN	Back-Propagation Neural Network
CCTV	Closed-Circuit Television
CNN	Convolutud Neural Network
CT	Computed Tomography
EEG	Electroencephalogram
FEA	Finite Element Analysis
GMR	Giant Magneto Resistive
GA	Genetic Algorithm
GP	Gaussian Process
GPU	Graphics Processing Unit
GVM	Gauss von Mises
LASSO	Least Absolute Shrinkage and Selection Operation
MAP	maximum a posteriori

MET	Minimum Error Thresholding
MFL	Magnetic Flux Leakage
MI	Mutual Information
MPMS	Magnetic Property Measurement System
MRI	Magnetic Resonance Imaging
MSE	Mean Square Error
MUMPS	MULTifrontal Massively Parallel sparse direct Solver
NDE	Non-Destructive Evaluation
NDT	Non-Destructive Testing
NN	Neural Network
NMI	Normalised Mutual Information
PCA	Principal Component Analysis
PDF	Probability Density Function
PDE	Partial Differential Equations
PEC	Pulsed Eddy Current
PIG	Pipeline Inspection Gauge
PLL	Phase-Locked Loop
RAM	Random Access Memory
RBF	Radial Basis Functions
RFEC	Remote Field Eddy Current
RFT	Remote-Field Technologies
RIMLS	Robust Implicit Moving Least Squares

ROC	Receiver Operating Characteristic
ROI	Region of Interest
ROR	Radius Outliers Removal
SLAM	Simultaneous Localisation and Mapping
SOR	Statistical Outliers Removal
SQUID	Superconducting QUantum Interference Device
SVM	Support Vector Machine
VIE	Volume Integral Equation
XRF	X-ray fluorescence

Nomenclature

General Formatting Style

Symbol

x	A scalar
\boldsymbol{x}	a vector
\boldsymbol{X}	a matrix
$\hat{[\cdot]}$	estimated parameter
$\bar{[\cdot]}$	mean value
$[\cdot]^{\dots}$	the superscript is used to describe the parameter
$[\cdot]_{\dots}$	the subscript is used as an indice
$[\cdot]^T$	transpose of a vector or a matrix
$\ \cdot \ $	norm of a vector

General Notations

\boldsymbol{E}	electric field
\boldsymbol{D}	electric displacement
\boldsymbol{P}	polarization
χ_e	electric susceptibility
ϵ	electric permittivity
ϵ_0	electric permittivity of free space
ϵ_r	relative electric permittivity
\boldsymbol{B}	magnetic field

H	H-field
M	magnetization
χ_m	magnetic susceptibility
μ	magnetic permeability
μ_0	magnetic permeability of free space
μ_r	relative magnetic permeability
A	vector potential
S	Poynting vector
σ	electrical conductivity
ω	circular frequency
λ	wavelength
l_{max}	mesh length
x	axial coordinate
θ	circumferential coordinate
j	complex number
y	sensor measurement
φ	signal phase-shift
t	local pipe thickness
w_i	model's parameter
w	set of all the model's parameter
T	thickness's matrix

Glossary of Terms

Double through-wall crossing	(p.30)
Exciter coil	(p.21)
Receiver coil	(p.21, p.24-p.26)
Phase-Knot	(p.28)
Poynting vector	(p.28, 73-75)
Near-field zone	(p.29)
Transition zone	(p.29)
Remote-field zone	(p.29)
Eddy currents	(p.17)
Maxwell equations	(p.15)
Constitutive equations	(p.15)

