Non-destructive data fusion from ultrasonic and eddy current testing using artificial neural networks

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Outline

Context and aim

Non destructive testing is widely used in many fields to detect flaws in :

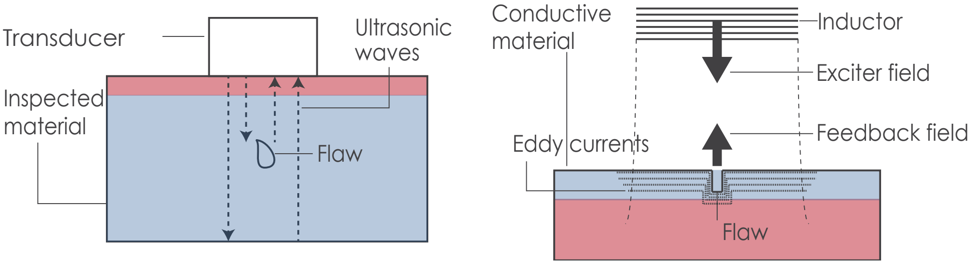
- Building materials
- Transport
- Aeronautics
- Aerospace

Most common techniques :

- Visual inspection
- **Ultrasonic waves**
- **Eddy currents**
- Thermography

Context and aim

The aim of this work is to combine both **ultrasonic and eddy current testing** using data fusion algorithms in order to detect flaws in a more reliable way



Data fusion is the combination of information from different sources in order to obtain information more accurate, reliable and at lower cost.

Simulated data base

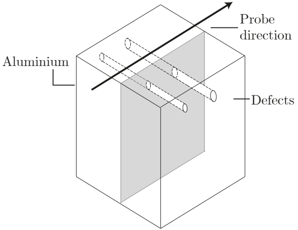
Why a data base is needed ?

- Obtain **ultrasonic and eddy current data from the same defects** to study the complementary of these techniques
- Use those data to develop and test **data fusion algorithms**
- Develop **inversion algorithms** with or without data fusion

How to obtain these data ?

- Through experimentation
  - Limited number of cases
- Simulated inspections
  - Control over data and defects : 256 cylindrical defects from 0.5 to 8 mm depth and radius by 0.5 mm step

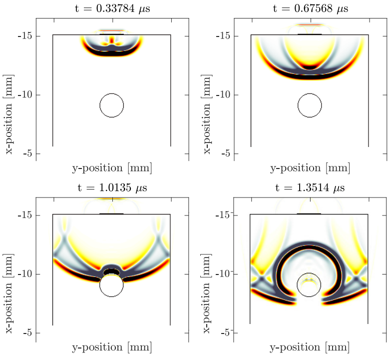
Simple cases : homogeneous aluminum blocks with simple defect geometries



Simulating ultrasonic data : K-WAVE simulator

Open source toolbox : **Mechanical wave propagation** [1] through pseudo-spectral finite difference method

- Homogeneous and isotropic medium
- Longitudinal waves



Transducer
- Radius of 6.35 mm (0.25 in)
- One measure each 5 mm

Signal
- F = 5 MHz, $\lambda = 1.2$ mm
- Five cycles pulses

Material
- Aluminum block
- 6400 m.s^{-1} longitudinal wave speed

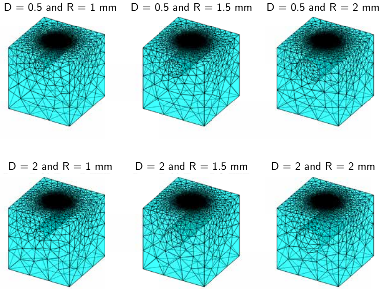
Grid
- 24 points per wavelength
- 20 samples per period

1. TREEBY, B., COX, B. et JAROS, J., *k-Wave, A MATLAB toolbox for the time domain simulation of acoustic wave field*, 2012

Simulating eddy current data : Finite element approach

Finite element method calculations : **Quasi-static electromagnetic waves**

- Two **complementary formulations A-φ** and **T-Ω** [2]



Coil
- Radius of 4 mm
- 250 spires
- One measurement each 5 mm

Signal
- F = 1 kHz, $\delta = 2$ mm
- Excitation I_{eff} = 1 A

Mesh
- 80000 elements
- Maximal density near the coil

Material
- Aluminum block
- Conductivity 37.7 MS/m
- $\mu_r = \epsilon_r = 1$

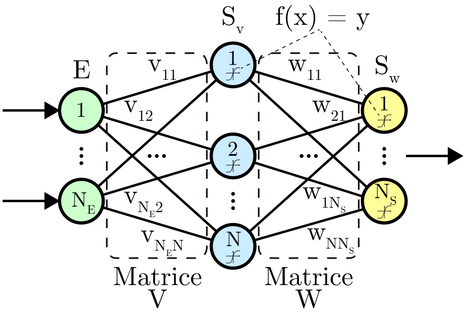
2. Henneron, T., « Contribution à la prise en compte des Grandeurs Globales dans les Problèmes d'Electromagnétisme résolus avec la Méthode des Eléments Finis », thèse de doct., Université Lille1 - Sciences et Technologies, 2004

Data fusion with artificial neural networks

Feed Forward Neural Network (FFNN)

- It can **approximate complex functions** [3]
- **No need for analytic or experimental model**
- It needs a learning data-set

Eddy current signals
+
Ultrasonic signals



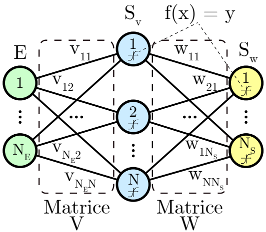
Radius and depth of defects

3. Rumelhart, D. E., Hinton, G. E. et Williams, R. J., « Learning internal representations by error propagation »„ n° V, 1985.

Network architecture

Architecture

- 33 inputs (3 features × 11 positions)
- 10 hidden neurons
- 2 outputs (radius and depth predictions)



Parameters

- Activation functions **Tansig** and **Pureline** : $f_1(x) = \frac{2}{(1+e^{-2x})} - 1$ and $f_2(x) = ax + b$
- Optimization algorithm : **Bayesian regularization backpropagation** [4]
- Data base split : 70% training, 15% validation and 15% test

4. Hagan, M. T., Demuth, H. B. et Beale, M. H., « Neural Network Design », *Boston Massachusetts PWS*, t. 2, p. 734, 1995.

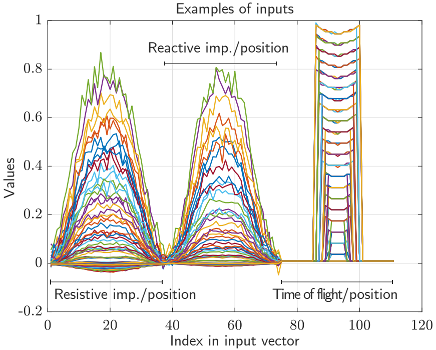
Network inputs/outputs

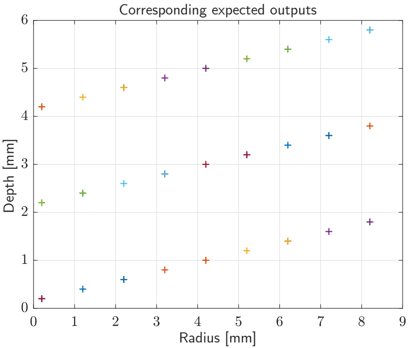
Input data / Expected outputs

- Vector containing eddy current and ultrasonic data for each sensor position along inspected block

$\Rightarrow$

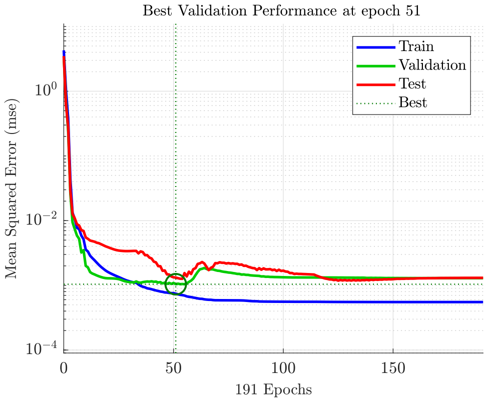
- Flaw radius
- Flaw depth

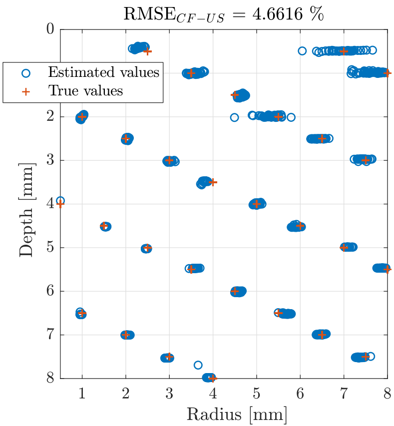




Performances on simulated data : training and test

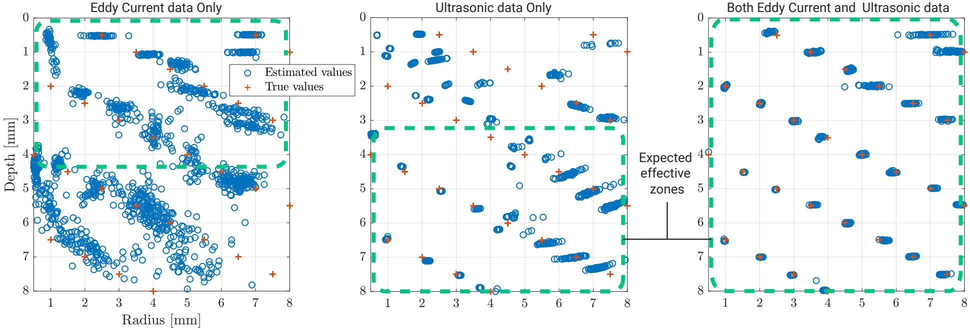
- Network is trained with the training set (70%)
- Validation set (15%) allows to keep best prediction capabilities
- Performances of the network are computed with test set (15%) : **RMSE < 5 %**





Results using data fusion

Results obtained on test data using neural networks trained with : eddy current data only, ultrasonic data and the data fusion US-ED



- **Complementarity** inspection methods
  - Eddy current : Skin effect limitation
  - Ultrasonic testing : Near field limitation
  - Both : Better predictions

Conclusion and future work

- Data fusion with multi-layers neural network
  - Allows to detect flaws in a more reliable way and in the all data-set range overcoming the limitations of ultrasonic waves and eddy currents

- Future work :
  - Testing the trained network using experimental data as input
  - Optimization algorithms to better fit experimental conditions
  - Investigating more complex materials

Thank you for your attention