Application of Kernel Change Detection Method in Eddy Current Non-destructive Testing

Majda KERMADI 1, Saïd MOUSSAOUI 2, Abdelhalim TAIEB BRAHIMI 1 and Mouloud FELIACHI 3

1 Electrical Department, University of Sciences and Technology of Oran, BP 1505, El M’Naouer, Oran 31000, Algeria majda.kermadi@univ-usto.dz, abdelhalim.taiebbrahimi@univ-usto.dz
2 IRCCyN, UMR CNRS 6597, Central School of Nantes, Nantes 44321, France Said.Moussaoui@irccyn.ec-nantes.fr
3 PRES-L’UNAM, IREENA Lab., IUT of Saint-Nazaire, University of Nantes Saint Nazaire 44600, France Mouloud.Feliachi@univ-nantes.fr

Abstract
This paper presents an adaptation of kernel change detection (KCD) method, that belongs to the family of abrupt change detection methods built on single-class ν-Support vector machines, in order to solve the problem of defect localization in eddy current non-destructive testing (NDT), the main aim of the work is the improvement of the computing time of the data processing algorithm by reducing the number of cost function evaluations. The KCD algorithm is modified and used to detect the damaged area in an electric conductive tube using eddy-current probe signal, the forward model linking measurements to electromagnetic properties of the tube is solved using a finite element method (FEM). The use of a defect localization step permits to reduce the number of measurement data that will be processed in defect characterization step. Simulation results show the efficiency of the proposed adaptation of the KCD algorithm in terms of defect localization and computing time reduction for the estimation of its geometrical parameters.

Keywords: eddy current testing, finite element method, inverse problem, kernel change detection.

1. INTRODUCTION

Non-destructive testing (NDT) aims to inspect materials integrity without destroying the functionality of the component or the system [1]. There are several sensing methods in NDT which are based on different measuring modalities. The focus of this paper is on Eddy Current testing that allows treating surface flaws or relatively close to the surface of the material [2]. The detection in this technique is based on the fact that the electromagnetic parameters of the material are disrupted by the presence of the defect. To solve the defect characterization problem, two main problems should be treated: the resolution of the forward problem, which consists in calculating the electromagnetic field knowing all geometric and electromagnetic parameters of the diagnosed surface, and the inverse problem which consists in using the measured impedance signal to deduce the geometric parameters (location, size and shape) and/or electromagnetic parameters (permittivity, conductivity ...) of the material.

To solve the inverse problem in non-destructive testing, we generally go through these three steps: detection, location, and characterization. Detection aims to recognize the presence of a defect, location permits to find the damaged area, characterization step aims at finding geometrical dimensions of the defect. Actually, the localization step is very useful for the reduction of the computation time by avoiding the treatment of all data for the characterization step. Actually, each data point needs the solving of the forward problem.
The resolution of the inverse problem of defect localization and characterization in Eddy-current testing (ECT) is a longstanding challenge [3, 4, 5, 6]. Machine learning methods applied in ECT have been also used for defects characterization in [3, 4, 5]. The most issue encountered in the inversion process is the expensive computing time due to the electromagnetic model simulation in the forward problem. In this paper our objective is to reduce the calculation time by using a kernel detection method KCD proposed in [9], to locate the damaged area and to apply the defect characterization algorithm to the data acquired in the neighborhood of the detected defect. In other words, the sensing data are selected so as it will be easier to estimate defects characteristics using a global optimization method such as particle swarm optimization [12, 13], used for flaw characterization in [7, 8].

However, the application of the KCD algorithm for the defect localization is not straightforward since the impedance variation does not present abrupt changes. So, an improvement of the detection index is presented and an optimization criterion is adopted to maximize the sparsity of this detection function.

The rest of this paper is organized as follows. We firstly present, in Section 2, the forward problem, its resolution using a Finite Element Method (FEM) and its numerical simulation for probe impedance calculation. Then the inverse problem of defect localization and the proposed application of the KCD algorithm for the defect localization in the context of EC-NDT are discussed in Section 3, where an adaptation is proposed in order to improve its efficiency. Section 4 gives some numerical results illustrating the usefulness of the proposed approach and the efficiency of defect characterization with Particle Swarm Optimization (PSO) algorithm. Finally, some conclusions are drawn in Section 5.

2. THE FORWARD PROBLEM

We consider in our application a non-destructive testing axisymmetric problem where a conductive tube is affected by two internal grooves with different dimensions, we also assume that the longitudinal sections of the grooves have a rectangular shape and are characterized by their Positions ($P_1 = 10mm, P_2 = 25mm$), Depths ($D_1 = 0.85mm, D_2 = 0.508mm$) and Lengths ($L_1 = 5mm, L_2 = 3mm$).

The sensor is a differential probe moving along the tube (see Figure 1).

Figure 1 show the retained sensing configuration where the differential probe constituted by two coils allows measuring the impedance variation along the probed tube made of INCONEL 600 [15].

The geometrical and the electromagnetic properties of the coils and the tube are summarized in Table 1.
According the eddy current sensing principle [6], the axisymmetric diffusion equation can be expressed in variational terms by the following energy function

\[
F = \int \left[ \frac{1}{2\mu} \left( \frac{1}{r} \frac{\partial (\mathbf{r} \cdot \mathbf{A})}{\partial r} \right)^2 + \frac{1}{\sigma} \left( \frac{\partial \mathbf{A}}{\partial z} \right)^2 \right] + \frac{j\omega\sigma}{2} |\mathbf{A}|^2 - J_s A \right] 2\pi r dr dz
\]  

(1)

Where the three energy terms of the integrand appearing in equation (1) correspond respectively to the magnetic field, Eddy current and source current.

A Finite Element (FE) method permits to compute the magnetic vector potential \( \mathbf{A} \) which allows to calculate the impedance. In fact, the impedance of a circular filament of radius \( r_i \) is calculated from the magnetic vector potential \( A_i \) at \( r_i \) and the value of current injected into the coil \( I_s \) as follows:

\[
Z_i = -\frac{E}{I_s} \frac{\partial \phi}{\partial z} = \frac{j\omega.2\pi r_i A_i}{I_s}
\]

(2)

The total impedance expression of circular coil whose section is discretized in \( N \) triangular elements is given by:

\[
Z = \frac{j\omega.2\pi N_s}{I_s} \sum_{i=1}^{N} r_{ci}. A_{ci} \Delta_i = \frac{j\omega.2\pi J_s}{I_s} \sum_{i=1}^{N} (r_{ci} \Delta_i). A_{ci}
\]

(3)

Where:

- \( N_s \): Turns density [Turns/m²]
- \( \Delta_i \): Surface of the i-th element.
- \( r_{ci}, A_{ci} \): Central values of \( r, A \) in the i-th element [6].

Actually, the differential probe is moving along the tube with the step size of \( \Delta x = 0.1 \text{ mm} \), which means that the surface to be scanned consists of \( n = 400 \) measured impedance values.

### 3. LOCALIZATION ALGORITHM

The differential probe is moving along the tube to measure the impedance variations \( \Delta Z_k \) at each point \( k = 1, ..., n \), the total impedance of differential probe can be obtained by summing the impedance of each coil.

To solve the defect localization problem we use an abrupt change detection algorithm which is applied to the probe impedance variations signal.
3.1 The Kernel Change Detection (KCD)

The Kernel Change Detection KCD algorithm was originally presented in [9]. It is a signal processing method that detects abrupt changes in a time series, and which compares the immediate past set and the immediate future set extracted on-line.

To summarize the principle of the KCD algorithm, we have to introduce the general framework of an on-line abrupt detection. Thus, let’s consider a time instant $t$, the training set of size $m_1, m_2$, and the two data subsets $x_{t,1} = \{x_i\}_{i=t-m_1,...,t-1}$, $x_{t,2} = \{x_i\}_{i=t,...,t+m_2-1}$ (see Figure. 2).

![Figure 2: General abrupt change detection framework.](image)

Let $t$ be some time instant and assume that the samples in $x_{t,1}$ (resp. in $x_{t,2}$) are sampled i.e. according to some Probability Density Function (PDF) $p_1$ (resp. $p_2$), these two hypotheses are obtained:

\[
\begin{align*}
H_0: & \quad p_2 = p_1, & (\text{No abrupt change}) \\
H_1: & \quad p_2 \neq p_1, & (\text{An abrupt change})
\end{align*}
\]

(4)

This test (equation 4) cannot be applied in practice. Though, since the Probability Density Functions $p_1$ and $p_2$ are not known. Some dissimilarity measure are used between $p_1$ and $p_2$, estimated from the sets $x_{t,1}$ and $x_{t,2}$.

Let $D(x_{t,1}, x_{t,2})$ be a dissimilarity measure between the sets $x_{t,1}$ and $x_{t,2}$, the problem defined in equation (4) can be expressed as follows [9]:

\[
\begin{align*}
H_0: & \quad D(x_{t,1}, x_{t,2}) \leq \eta, & (\text{No abrupt change}) \\
H_1: & \quad D(x_{t,1}, x_{t,2}) > \eta, & (\text{An abrupt change})
\end{align*}
\]

(5)

Where $\eta$ represents the threshold that tunes the sensibility/robustness compromise. The detection performances requires the dissimilarity measure $D(\cdot, \cdot)$ that compares the sets of $x_{t,1}$ and $x_{t,2}$. More precisely, if $x_{t,1}$ and $x_{t,2}$ occupy the same region of the space $X$, the relevant $D(\cdot, \cdot)$ should give low values, and large values if $x_{t,1}$ and $x_{t,2}$ occupy distinct regions.

We consider the analysis time $t$, and let assume that two single-class classifiers are trained independently on the sets $x_{t,1}$ and $x_{t,2}$, yielding two regions $R^X_{x_{t,1}}$ and $R^X_{x_{t,2}}$, or, equivalently in feature space $H$, two hyper-planes $\mathcal{W}_{t,1}$ and $\mathcal{W}_{t,2}$ parameterized by $(w_{t,1}, \rho_{t,1})$ and $(w_{t,2}, \rho_{t,2})$. In $H$, the vectors $w_{t,1}$ and $w_{t,2}$ define a 2-dimensional plane, denoted $P_t$, that intersects the hypersphere $S$ along a circle with center $O$ and radius 1, as described in Figure 3. In fact, in the least probable case where $w_{t,1}$ and $w_{t,2}$ are collinear, there is an infinity of planes $P_t$, and one can select any of them [9].
In feature space, the plane $W_{t,1}$ (resp. $W_{t,2}$) bounds the segment of $S$ where most of the mapped points in $x_{t,1}$ (resp. $x_{t,2}$) lie.

The dissimilarity measure is calculated by comparing the arc $c_{t,1}^{-}c_{t,2}^{+}$ between $\langle w_{t,1}, w_{t,2} \rangle$ to the sum of two arcs $c_{t,1}^{-}\tilde{p}_{t,1}$ and $c_{t,2}^{+}\tilde{p}_{t,2}$ at $t$, as defined below [9]

$$D_H(x_{t,1}, x_{t,2}) = \frac{c_{t,1}^{-}c_{t,2}^{+}}{c_{t,1}^{-}\tilde{p}_{t,1} + c_{t,2}^{+}\tilde{p}_{t,2}}$$

(6)

Where:

$$c_{t,1}^{-}c_{t,2}^{+} = \arccos\left(\frac{\langle w_{t,1}, w_{t,2} \rangle_H}{\|w_{t,1}\|_H\|w_{t,2}\|_H}\right)$$

(7)

$$c_{t,1}^{-}\tilde{p}_{t,1} = \arccos\left(\frac{\rho_{t,i}}{\alpha_{t,i}\kappa_{t,i}\alpha_{t,i}}\right), \; i = \{1,2\}$$

(8)

With $\alpha_{t,i}$: a column vector containing the $w_{t,i}$ (resp. $w_{t,i}$) parameters. More details and explanations about the KCD algorithm are present in [9] [10].

4. SIMULATION RESULTS

The KCD algorithm was applied to a simulated data according to the sensing configuration illustrated in Figure 1. The absolute value of impedance variation signal $|\Delta(Z)|$ is used as the input data for solving the defect localization problem.

The design parameters of the KCD algorithm are summarized in Table 2: The dispersion parameter $\sigma$ for the Gaussian kernel, the parameter of regularization $\nu$, the training set size $m$ and the detection threshold $\eta$. 
The Gaussian kernel expression is described as follows:

\[
k_\sigma(x, x') = \exp \left( -\frac{\|x-x'\|^2}{2\sigma^2} \right)
\]  

(9)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma)</td>
<td>10</td>
</tr>
<tr>
<td>(\nu)</td>
<td>0.5</td>
</tr>
<tr>
<td>(\eta)</td>
<td>5</td>
</tr>
<tr>
<td>(\omega)</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 2: parameters values of KCD algorithm.

Figure 4 shows the input data and the resulting KCD index. One can see in Figure 4 (top) that changes in \(|\Delta(Z)|\) signal are not abrupt; contrary they present a slow variation. Hence classical KCD algorithm could not continuously detect changes (see Figure 4 (bottom)).

4.1 Adaptation of the KCD algorithm

In order to account for the slow variation of the input signal, the KCD algorithm is modified so as to compare more distant frames of the measured probe impedance (see Figure 5).

Figure 5: Framework adopted for the modified on-line kernel change detection algorithm.
We introduce a horizon equal to $2h$ between the two distant frames of the signal: $x_{t,1} = x_{t-m-h}, ..., x_{t-h-1}$ and $x_{t,2} = x_{t+1+h}, ..., x_{t+m+h}$. Such modification allows comparing different parts of the signal, which will exhibit more abrupt changes than in the case of successive frames.

To validate the proposed modification of the KCD algorithm we compute a novel KCD index for both $h = 7$ and $h = 13$ (see Figure 6).

![Figure 6: $|\Delta(Z)|$ signal (top), Index KCD associated for $h=5$ and $h=10$ (bottom).](image)

We notice an improvement when we introduce the horizon $h$. However, the choice of the value of the horizon $h$ should be set to optimize the detection performances.

4.2 Optimization of the detection index

Since the KCD index will be used to detect the location of the abrupt changes, it should therefore be zero (or take small values) unless when the change occurs. Such property can be measured using the concept of sparsity. In that respect, the best value of $h$ should lead to the sparsest index

$$h = \arg\min_h S(I)$$

Where the sparsity measure is defined by [11]

$$S(I) = \left( \frac{\sum_{k=1}^n I_k(h)}{\sqrt{\sum_{k=1}^n (I_k(h))^2}} \right)$$
Figure 7 provides the evolution of the KCD index with respect to the value of $h$. It can also be noted that the best value is $h=20$.

We present thereafter kernel change detection index for $h=20$ (Figure 8).

Results shown in Figure 8 (bottom) prove the efficiency of the proposed method for detecting slow variations of the impedance signal. We can extract the beginnings and the ends of the damaged zones according to the peaks that show KCD index with a threshold value $\eta = 20$.

4.2 Defect characterization

We apply the PSO algorithm for defect characterization by estimating position, depth and
length of two axisymmetric grooves, the dimensions of the defect are fixed, and adjusted iteratively. Particle swarm optimization is a heuristic global optimization method. It was developed in 1995 by Russel Eberhart and James Kennedy [12]. It can be used to explore the search space of any problem to find the set of parameters that minimize/maximize an objective.

In PSO the position of each particle in the swarm is updated in order to perform its next movement by adjusting its actual velocity $v_i(t)$ at $t$, its best performance $Pb_i$ and the best performance in the swarm $Pg_i$ according to these following equations [13, 14]:

$$v_i(t + 1) = wv_i(t) + c_1r_1(Pb_i - x_i(t)) + c_2r_2(Pg_i - x_i(t))$$  \hspace{1cm} (12)

$$x_i(t + 1) = x_i + v_i(t + 1)$$  \hspace{1cm} (13)

Where:
- $v$: particle velocity, $x$: particle position , $r_1, r_2$: random numbers generated from the interval $[0,1]$, $c_1, c_2$: cognitive and social acceleration coefficients, $w$: inertia factor .

The particle swarm optimization algorithm parameters are choose from the literature [12], and are summarized in Table 3.

<table>
<thead>
<tr>
<th>PSO coefficient</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1, c_2$</td>
<td>1.4</td>
</tr>
<tr>
<td>$w_{max}$</td>
<td>0.9</td>
</tr>
<tr>
<td>$w_{min}$</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Table 3: PSO algorithm parameters.

We present in Table 4 the performances of the PSO algorithm :

<table>
<thead>
<tr>
<th>Defects</th>
<th>Estimated position</th>
<th>Estimated length</th>
<th>Estimated depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Defect 1</td>
<td>10 mm</td>
<td>5mm</td>
<td>0.834mm</td>
</tr>
<tr>
<td>Defect 2</td>
<td>25.03mm</td>
<td>2.99mm</td>
<td>0.509mm</td>
</tr>
</tbody>
</table>

Table 4: defect estimated parameters.

Particle swarm optimization method applied to characterization of the two defects shows good results with a very weak and acceptable uncertainty. However, it still suffers from a long computing time.

5. CONCLUSIONS
An adaptation of the KCD algorithm has been proposed for detecting slow variations in Eddy current non-destructive testing (EC-NDT). We first solved the forward problem where a plate is affected by two internal grooves with finite element method FEM and compute the probe impedance variation which we use after as an input for the KCD algorithm, in order to extract the damaged zones in the tube from probe impedance variations signal. The application of the proposed KCD algorithm to Eddy current testing signal showed good results.

A numerical example shows the performances of this proposed method which is considered as a first step for inverse problem solution in order to reduce time computation and a number of cost function evaluations for flaw characterization in optimization step.

REFERENCES


