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Application of Kernel Change Detection Method in Eddy Current Non-destructive Testing (EC-NDT)

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Abstract

This paper presents an adaptation of kernel change detection (KCD) method to solve the problem of defect localization in non-destructive testing (NDT). The main outcome is the improvement of the computing time of the data processing algorithm by reducing the number of cost function evaluations. The KCD algorithm is adapted and used to detect the flawless area in a conductive plate using eddy-current testing signals, more precisely impedance measurements. The forward model linking measurements to electromagnetic properties of the plate is solved using a finite element method (FEM). The use of a defect localization step leads to reducing the number of measurement data that will be processed in order to solve the inverse problem of defect characterization. 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 NDT techniques based on different measuring modalities and signal processing methods. The focus of this paper is on Eddy Current testing (ECT) 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 (mainly permittivity and conductivity) of the defect.

Non-destructive testing techniques are generally carried out in three steps: detection, location, and characterization. Detection aims to recognize the presence of a defect, location permits to determine 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 the whole collected data for the characterization step. Actually, each data point necessitates the solving of the forward problem and using the whole data set will induce a prohibitive computing time. The resolution of the inverse problem of defect localization and characterization in Eddy-current testing is a longstanding challenge and several methods have been proposed in a number of papers [3, 4, 5, 6].

Explain the principle of these methods, their drawbacks and limitations and why there is a need to develop additional methods

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 [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 [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 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. Finally conclusion is drawn in Section 5.

2. THE FORWARD PROBLEM

We consider an axisymmetric non-destructive testing problem where a conductive plate is affected by two internal cracks having different geometries. We also assume that the defects 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 plate (see Figure. 1).

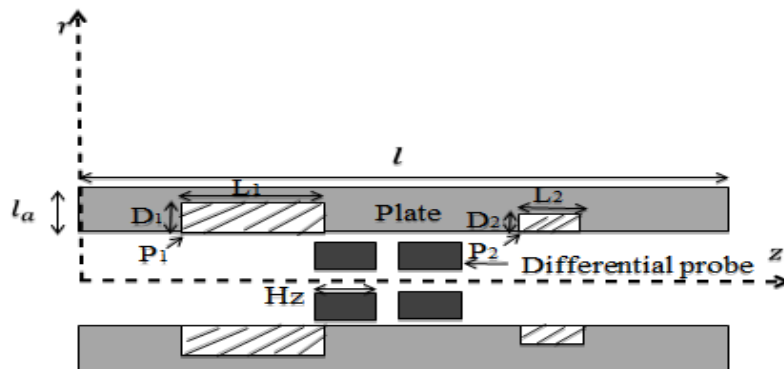


Figure 1: Schematic drawing of the geometry.

Figure 1 shows the retained sensing configuration where the differential probe constituted by two coils allow measuring the impedance variation along the probed plate. The geometrical and the electromagnetic properties of the coils and the plate are summarized in Table 1.

Coil	Descriptions
Inner radius	7.75 mm
Outer radius	8.5 mm
Height along z	0.75 mm
Distance to the plate	0.1 mm
Number of turns	70
Frequency	100 kHz
Plate	Descriptions
Width	1.27 mm
Length	40 mm
Conductivity	10^6 S/m
Relative permeability	1

Table 1: Coil and plate parameters.

According the Eddy current sensing principle [4], the axisymmetric diffusion equation can be expressed in variational terms by the following energy function

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

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 \vec{A} which allows to calculate coil impedance.

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:

$$Z_i = -\frac{E}{I_s} = \frac{\partial \phi}{\partial t} = \frac{j\omega \cdot 2\pi \cdot r_i \cdot A_i}{I_s} \quad (2)$$

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

$$Z = \frac{j\omega \cdot 2\pi \cdot N_s}{I_s} \sum_{i=1}^N r_{ci} \cdot A_{ci} \Delta_i = \frac{j\omega \cdot 2\pi \cdot J_s}{I_s^2} \sum_{i=1}^N (r_{ci} \Delta_i) \cdot A_{ci} \quad (3)$$

Where:

N_s : Turns density [turns/m²]

Δ_i : Surface of the i-th element.

r_{ci}, A_{ci} : Central values of r, A in the i-th element [4].

3. LOCALIZATION ALGORITHM

The differential probe is moving along the plate to measure variations of the coil impedance

ΔZ_k at each point $k = 1, \dots, n$, the total impedance of differential probe can be obtained by summing the impedance of each coil.

To solve inverse problem of defect localization we use an abrupt change detection algorithm which is performed to detect damaged zones from this impedance measurements.

The aim is to locate defects from this set of measured impedance variations, which is considered as the input data of the algorithm KCD.

3.1 Kernel change detection algorithm

Most of on-line detection techniques are special instances of the following generic framework: Consider time t and two descriptor subsets (the *immediate past* subset $x_{t,1} = \{x_i\}_{i=t-m_1, \dots, t-1}$ and the *immediate future* $x_{t,2} = \{x_i\}_{i=t, \dots, t+m_2-1}$, as represented in figure 3.

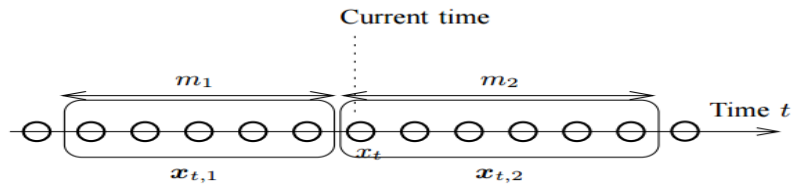


Figure 2: General abrupt change detection framework based on the time series of descriptors $x_t, t = 1, 2, \dots, n$ represented by circles.

The on-line abrupt change detection problem is described as follows:

Let t be some time instant and assume that the samples in $x_{t,1}$ (resp. in $x_{t,2}$) are sampled i.i.d. according to some probability density function (pdf) p_1 (resp. p_2). Then, one of the two hypotheses holds:

$$\begin{cases} H_0: p_2 = p_1, & \text{(No abrupt change occurs)} \\ H_1: p_2 \neq p_1, & \text{(An abrupt change occurs).} \end{cases} \quad (4)$$

This test cannot be applied in practice, however, since the pdfs p_1 and p_2 are not known. The standard practical approach uses some dissimilarity measure between p_1 and p_2 , estimated from the sole knowledge of the sets $x_{t,1}$ and $x_{t,2}$. Let $D(x_{t,1}, x_{t,2})$ be such a dissimilarity measure, the previous problem can then be written as follows:

$$\begin{cases} H_0: D(x_{t,1}, x_{t,2}) \leq \eta, & \text{(No abrupt change occurs)} \\ H_1: D(x_{t,1}, x_{t,2}) > \eta, & \text{(An abrupt change occurs).} \end{cases} \quad (5)$$

Where η , is a threshold that tunes the sensibility/robustness tradeoff, as in every detection framework.

The general framework for abrupt change detection requires the dissimilarity measure $D(\dots)$ aimed at comparing the sets of descriptors $x_{t,1}$ and $x_{t,2}$. More precisely, a relevant $D(\dots)$ should give low values whenever $x_{t,1}$ and $x_{t,2}$ occupy the same region of the space χ and large values whenever $x_{t,1}$ and $x_{t,2}$ occupy the distinct regions.

The Kernel Change Detection algorithm was originally presented in [6]. It belongs to the

family of abrupt change detection methods built on single-class ν -Support vector machines.

Considering the analysis time t . Assume that two single-class classifiers are trained independently on the sets $x_{t,1}$ and $x_{t,2}$, yielding two regions $R_{x_{t,1}}^X$ and $R_{x_{t,2}}^X$ or, equivalently in feature space H , two hyperplanes $W_{t,1}$ and $W_{t,2}$ 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 depicted in Fig. 3. Actually, in the least probable case where $w_{t,1}$ and $w_{t,2}$ are collinear (which is highly unlikely), there is an infinity of planes P_t , and one can select any of them.

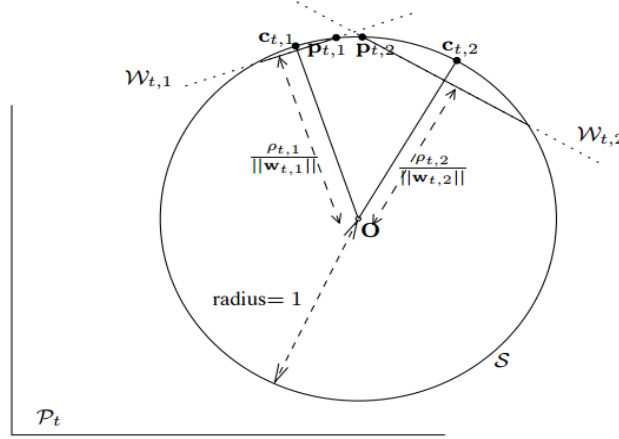


Figure 3: The SV single-class classifiers yield two regions $R_{x_{t,1}}^H$ and $R_{x_{t,2}}^H$ which are density support estimates in feature space. The circle represented corresponds to the intersection of the plane P_t (uniquely defined by $w_{t,1}$ and $w_{t,2}$) and S . The intersection of the (prolongated) vector $w_{t,1}$ (resp. $w_{t,2}$) with S yields $c_{t,1}$ (resp. $c_{t,2}$), and the intersection of the hyperplane $W_{t,1}$ (resp. $W_{t,2}$) with S in the plane P_t yields two points, one of which is denoted $\rho_{t,1}$ (resp. $\rho_{t,2}$). The situation plotted corresponds to an abrupt change, as both regions do not strongly overlap.

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 defined as [9]

$$D_H(x_{t,1}, x_{t,2}) = \frac{c_{t,1} \widehat{c_{t,2}}}{c_{t,1} \rho_{t,1} + c_{t,2} \rho_{t,2}} = \quad (6)$$

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 the solving of the defect localization problem.

The design parameters of the KCD algorithm are summarized in Table 2: The dispersion parameter σ for the Gaussian kernel, the parameter of regularization ν , the training set m and the threshold η .

Parameters	Values
σ	10
ν	0.5

m	5
η	20

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 detect real changes (see Figure 4 (bottom)).

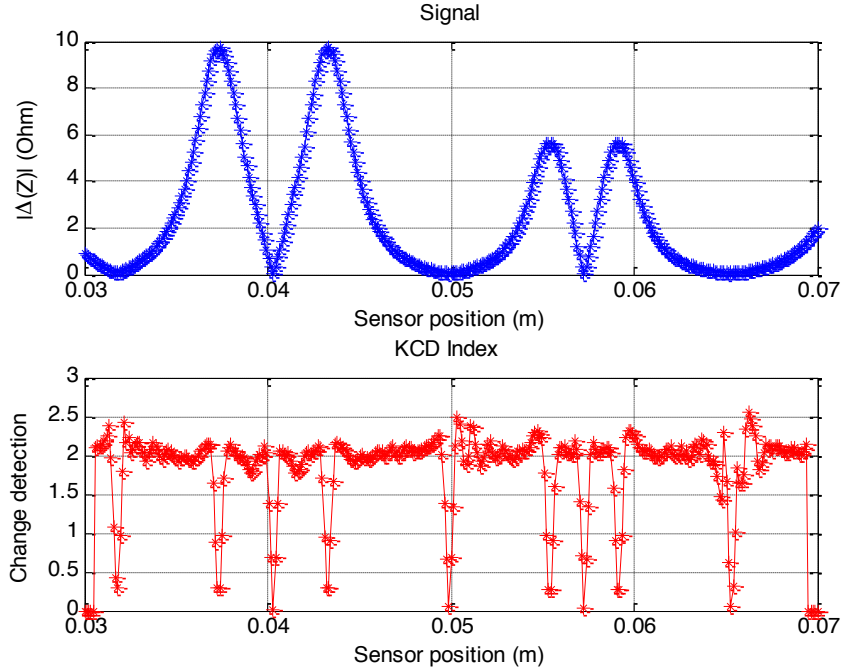


Figure 4: $|\Delta(Z)|$ signal (top), Index KCD associated (bottom).

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 input impedance variation (see figure 5).

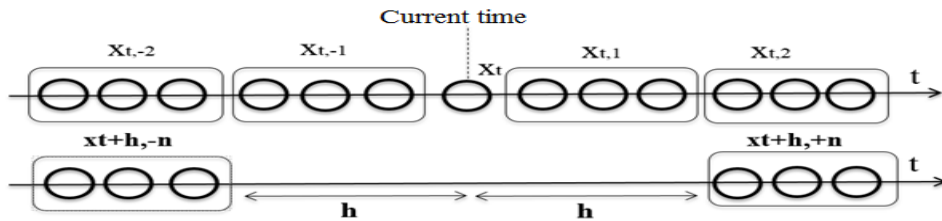


Figure 5: Framework adopted for detecting ruptures Online (After modification).

We introduce a horizon equal to $2h$ between the two distant frames of the signal: $x_{t,1} = x_{t-m-h}, \dots, x_{t-h-1}$ and $x_{t,2} = x_{t+1+h}, \dots, x_{t+m+h}$. 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 $h = 5$ and $h = 10$ (see Figure 6). We notice an improvement when we introduce horizon h . However, the choice of the value of the horizon h should be set to optimize the algorithm performances.

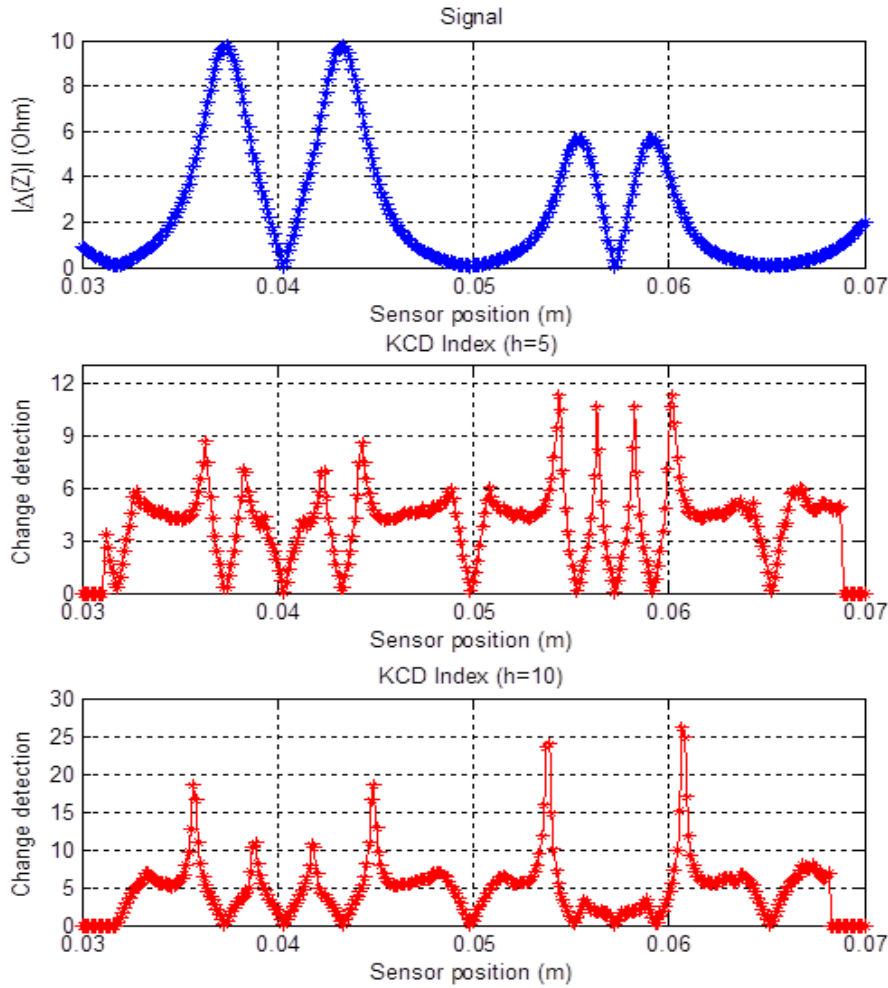


Figure 6: $|\Delta(Z)|$ signal (top), Index KCD associated for $h=5$ and $h=10$ (bottom).

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

$$h = \operatorname{argmin}_h S(I). \quad (7)$$

Where the sparsity measure is defined by [10]

$$S(I) = \left(\frac{\sum_{k=1}^n I_k(h)}{\sqrt{\sum_{k=1}^n (I_k(h))^2}} \right). \quad (8)$$

Figure 6 provides the evolution of the KCD index with respect to the value of h . It can also be noted that the best value is $h=20$.

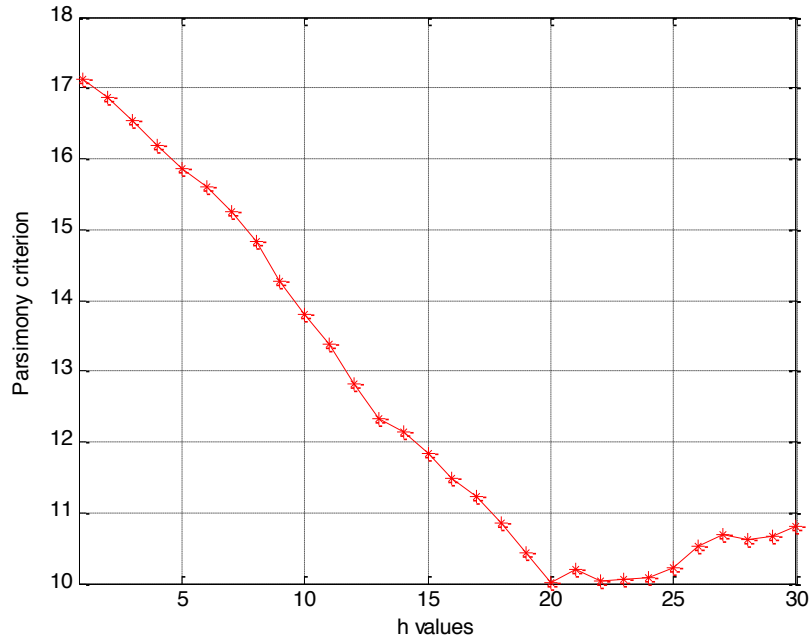


Figure 7: Sparsity criterion.

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

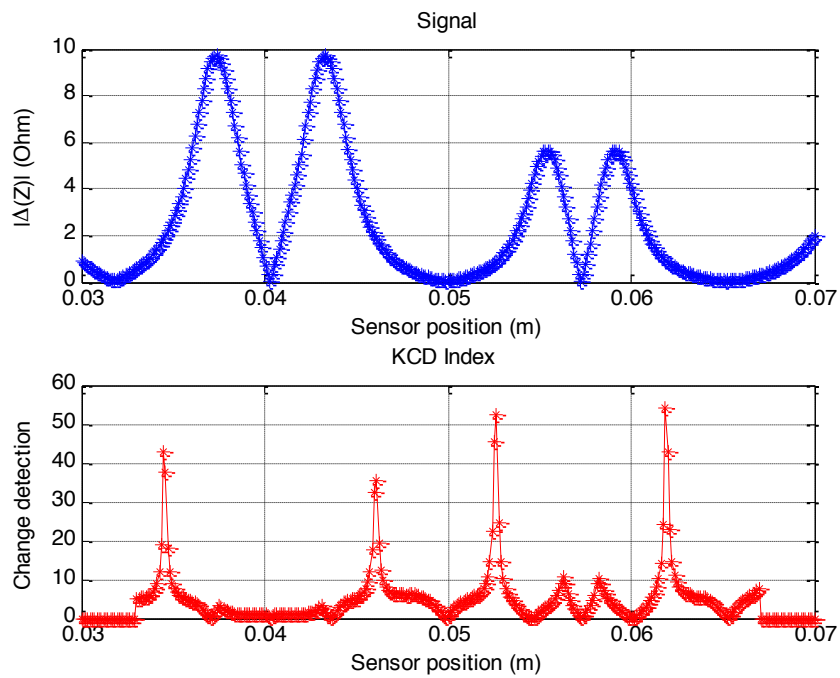


Figure 8: $|\Delta(Z)|$ signal (top), Index KCD associated after modification (bottom).
For a threshold $\eta = 20$.

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

4.2 Optimization results

We apply particle swarm algorithm [9] to defect characterization in order to estimate position, depth and length of two axisymmetric grooves.

Particle swarm optimization is a heuristic global optimization method. It was developed in 1995 by Russel Eberhart and James Kennedy [11]. 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 [12, 13]:

$$v_i(t + 1) = wv_i(t) + c_1r_1(Pb_i - x_i(t)) + c_2r_2(Pg_i - x_i(t)) \quad (9)$$

$$x_i(t + 1) = x_i + v_i(t + 1) \quad (10)$$

Where:

v : particle velocity, x : particle position, r_1, r_2 : random numbers generated from the interval $[0,1]$, c_1, c_2 : intensities of attraction towards P_b and P_g respectively, w : inertia factor (to control velocity).

The particle swarm optimization algorithm parameters are the same as those used in [7].

PSO coefficient	Value
c_1, c_2	1.4
w_{max}	0.9
w_{min}	0.4

Table 3: PSO algorithm parameters.

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

Defects	Estimated position	Estimated length	Estimated depth
Defect 1	10 mm	5mm	0.834mm
Defect 2	25,03mm	2,99mm	0.509mm

Table4: defect estimated parameters.

Particle swarm optimization method applied to characterization of the two defects shows good results with a very weak and acceptable uncertainty.

5. CONCLUSION

A novel KCD approach 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 impedance variation that we use after as an input for the KCD algorithm, to extract the damaged zones in the plate from impedance variations signal. The application of the proposed KCD algorithm to Eddy current testing signal showed good results.

A couple of numerical examples show 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 function evaluations for flaw characterization in optimization step.

6. REFERENCES

- [1] Jacques Rivenez, A Lambert « Les contrôles non destructifs. Généralités » 3ème édition revue et corrigée, CETIM, 1994.
- [2] Boeing, Eddy Current Familiarization Course, BOEING Commercial JET Nondestructive Test, 1991.
- [3] A. Bernieri, L. Ferrigno, M.Laracca and M. Molinara, “An SVM Approach to Crack Shape Reconstruction in Eddy Current Testing”, IMTC 2006 – Instrumentation and Measurement Technology Conference Sorrento, Italy 24-27 April 2006.
- [4] A. Bernieri, L. Ferrigno, Member and M. Laracca, Member, IEEE, and M.Molinara, “Crack Shape Reconstruction in Eddy Current Testing Using Machine Learning Systems for Regression”,IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT, VOL. 57, NO. 9, SEPTEMBER 2008.
- [5] R. Douvenot, M. Lambert and D. Lesselier, “Bases de données séquentielles et méthodes inverses appliquées au CND par courants de Foucault” Réunion plénière ” Interférences d’Ondes ” du GDR Ondes, Nov 2009, Paris, France.
- [6] Lee H-b., Jung H-K., Hahn S-y., “An Inverse Analysis for Crack Identification in Eddy Current NDT of Tubes”, IEEE Transactions on Magnetic, 30 (1994), NO. 5, 3403-3406.
- [7] A. Hamel, H. Mohellebi and M. Feliachi, “Imperialist Competitive Algorithm and Particle Swarm Optimization Comparison for Eddy Current Non-destructive Evaluation”, ISSN 0033-2097, R. 88 NR 9a/2012.
- [8] M. Cacciola, S. Calcagno, F.C. Morabito and M. Versaci “Swarm Optimization for Imaging of Corrosion by Impedance Measurements in Eddy Current Test”, IEEE TRANSACTIONS ON MAGNETICS, VOL., 43, NO.4, APRIL 2007.
- [9] F. Desobry, M. Davy and C. Doncarli, "An Online Kernel Change Detection Algorithm", IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 53, NO. 8, AUGUST 2005.
- [10] P. Hoyer, Non-negative Matrix Factorization with Sparseness Constraints, Journal of Machine Learning Research 5, 1457–1469 , (2004)
- [11] J. Kennedy and R. C. Eberhart, “Particle Swarm Optimization”, IEEE Int. Conf. Neural Networks, Perth, Aust., vol. 4, pp. 1942–1948, Jan. 1995.
- [12] Eberhart R.C, Kennedy J., A New Optimizer Using Particle Swarm Theory, proc. Sixth International Symposium on Micro Machine and Human Science (Nagoya, Japon), IEEE Service Center, Piscataway, (1995), NJ, 39-43.
- [13] Shi Y., Eberhart R.C., A Modified Particle Swarm Optimizer, proc. IEEE Congress on Evolutionary Computation, Piscataway, (1998), NJ, 69-73.