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# Support Vector Machines and Eddy-Current Tests for Flaws Characterisation in Thin Metallic Plates

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*Abstract:* - Eddy Current Techniques (ECT) for Non-Destructive Testing and Evaluation (NDT/NDE) of conducting materials is one of the most application-oriented field of research within electromagnetics. In this work, a novel approach is proposed to classify defects in metallic plates in terms of their depth starting from a set of experimental measurements. The problem is solved by means of a system based on wavelets approach extracting information on the specimen under test from the measurements and, then, implementing Support Vector Machines in order to determine its depth. Finally, Confusion Matrices (CMs) operators have been taken into account to improve the procedure.

*Key-Words:* - Defect classifying, NDT, wavelets transform, Support Vector Machines

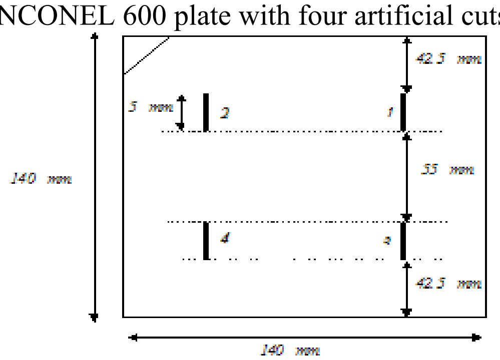
## 1 Introduction

NDT in the field of defects identification in metallic elements plays a remarkable role with special regard to those sectors where the integrity of the material is strictly required. As a consequence, the detection of defects in metallic plates together with the relevant shape classification provides the operator useful information on the actual mechanical integrity of the specimen [1]. It should be considered that defects rarely look as well-known geometrical shapes. At the state-of-the-art, non-destructive identification systems allow to locate a defect but without being capable to determine its shape. In addition, different defects give rise to totally similar signals. This paper aims to deal with the classification of defects, both Inner (ID) (the probe lies on the same side of the plate where the defect is located) and Outer (OD) ones (probe and defect are on opposite sides of the plate), in terms of their depth introducing an approach based on Support Vector Machines (SVMs) obtaining separation hyper-planes among data belonging to different classes. A previously proposed pre-processing based on Wavelet Transforms (WTs) is exploited to extract features related to the local trend of the signal. In this way, a device ables to classify defects into two macro-classes have been carried out. In order to refine the procedure, Confusion Matrix which evaluates the goodness of a trained classifier, has been taken into account. The conventional approaches to classification which assign a specific class for each defect are often inadequate because each defect may embrace more than a single class. Support Vector theory can provide a more appropriate solution to this problem. The paper is organized as follows: Section 2 reports the characteristics of the experimental database; Section 3 describes the theory of SVMs and the implementation procedure of our SVM-based classifier; Section 4 shows the WT approach for data pre-processing; in Section 5 the classification results are discussed and, finally, in Section 6 some conclusions are drawn.

## 2 The Building of Experimental Database

Experimental measurements have been carried out at Non Destructive Testing Lab, DIMET Department, University “Mediterranea” of Reggio Calabria, on a INCONEL 600 specimen (Fig. 1) from JSAEM (Japan Society of Applied Electromagnetics and Mechanics).

Fig. 1 - JSAEM sample (140 mm x 140 mm x 1.25 mm INCONEL 600 plate with four artificial cuts)




| crack | width [mm] | depth [mm] | length [mm] |
|---|---|---|---|
| 1 (40%) | 0.260 | 0.494 | 4.927 |
| 2 (100%) | 0.286 | 1.25 | 4.935 |
| 3 (20%) | 0.261 | 0.241 | 4.872 |
| 4 (60%) | 0.270 | 0.748 | 4.920 |

It’s a plate 140 x 140 x 1.25 mm with four artificial (EDM) 0.2 x 5 mm rectangular cuts having depths of 20%, 40%, 60% and 100% respectively of the plate thickness. The applied sensor was a FLUXSET®-type probe [2], moved over the specimen by means of a 0.5 mm-step automatic scanning procedure along x and y axes. A 70 x 70 mm central portion of the specimen was investigated this

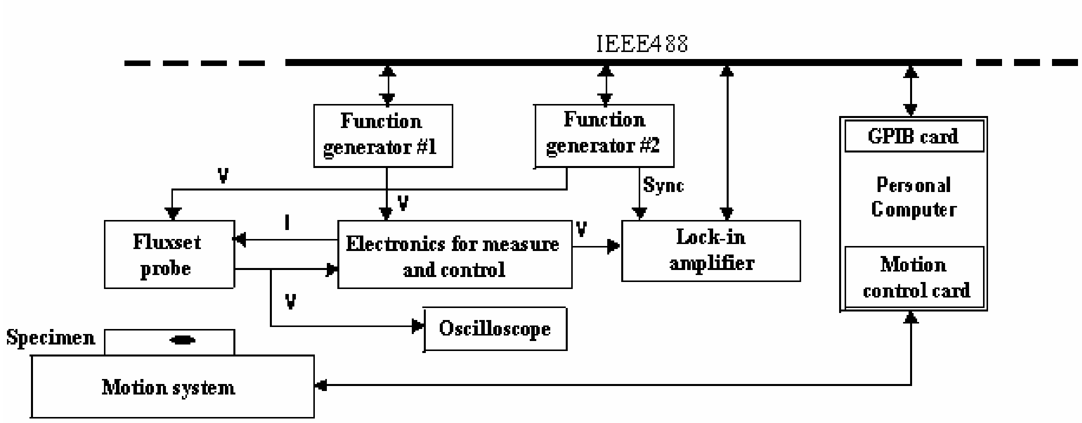



Fig. 2 – Block diagram of Fluxset device

way. A driving signal - triangular shape, 125 kHz frequency, 2Vpp amplitude - was applied to saturate the core material inside the probe. An external sinusoidal exciting field at a frequency of 1 kHz and a current of 107 mArms was generated close to the specimen, thus inducing eddy currents on the surface as well as on subsurface layers (Fig. 2). The output pick-up voltage is proportional to the radial component of the induced magnetic field; in the experimental arrangement this component coincides with the component parallel to the longitudinal axis of the sensor itself, that is *x* axis. 48 full scannings were run and the following 8 outputs were selected (inputs of SVM procedure): the module of the voltage (peak value $|V_{peak}|$, [mV]); the current applied by the signal generator $|i_{gen}|$, [mA]; the frequency of the sinusoidal signal $f_{signal}$, [kHz]; the five Wavelet Detail Coefficients (WDCs) concerning the region where a crack is found. Because the depth measured by the probe does not change during the scan of each defect (just the *y* position of the probe increases in 0.5 mm steps), the first two classes have been grouped to make a single class, and in the same way with the third and fourth classes. Each input pattern has been linked to a class codification (Table 1) representing the crack depth (output of FIS procedure). Fig. 3 shows the Eulero-Venn's diagram of classes, focusing on the intersection zone.

Table 1 – Codification of FIS' output

| Class | Codification of SVM |
|---|---|
| ID [20%÷60%], OD [60%÷20%] | 1 |
| ID [40%÷100%], OD [100%÷40%] | 2 |

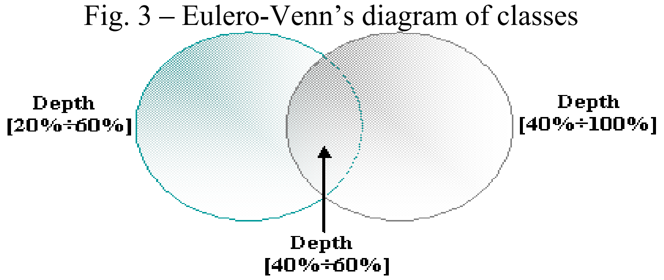



Fig. 3 – Eulero-Venn's diagram of classes

## 3 SVM: theory and classifiers

A support vector classifier attempts to locate a hyperplane that maximises the distance from the members of each class to the same hyperplane. BSVMs have been introduced within the framework of the Statistical Learning Theory [3],[4], which describes the principle of Structural Risk Minimization (SRM). Considering a support vector classifier [5], the error probability is upper bounded by a quantity depending by both the error rate achieved on the training set and a measure of the "richness" of the set of decision functions it can implement (named "capacity", or Vapnik Chervonenkis dimension). The more the set of decision functions is rich, the higher is the classifier's capacity, and the upper bound on the error probability can increase for increasing values of the capacity. This principle aims at reaching the minimum of the upper bound on the error probability of a classifier, by achieving a trade-off between the performance on the training set and the capacity. For a complete explanation, let us first consider a binary case: assuming that the training data with *k* number of samples is represented by $\{x_i, y_i\}$, i=1,…,k, where $\mathbf{x} \in \mathbf{R}^n$ is an n-dimensional vector and $y \in \{-1,+1\}$ is the class label. If these training patterns are linearly separable, we have to find a vector w (which determining the orientation of a discriminating plane) and a scalar *b* (which determine offset of the discriminating plane from origin) in order to satisfy the following inequalities:

$$\text{a) } \mathbf{w} \cdot \mathbf{x_i} + b \geq +1 \quad \textit{for all } y = +1$$
$$\text{b) } \mathbf{w} \cdot \mathbf{x_i} + b \leq -1 \quad \textit{for all } y = -1 \qquad (1)$$

So, we can find an Optimal Separation Hyperplane (OSH) which divides the data so that all the points with the same label lie on the same side of the hyperplane. Since the data are generally not linearly separable, a slack variable $\xi_i$, i=1,……,k, $\xi_i \geq 0$ has to be introduced [5], such that we can find a generalised OSH, also called Soft Margin Hyperplane (SMH), by solving the conditions:

$$\text{a) } \min_{\mathbf{w}, b, \xi_1, \ldots, \xi_k} \left[ \frac{1}{2} |\mathbf{w}|^2 + C \sum_{i=1}^{k} \xi_i \right]$$
$$\text{b) } y_i(\mathbf{w} \cdot \mathbf{x_i} + b) - 1 + \xi_i \geq 0 \qquad \xi_i \geq 0 \quad \text{i=1,...,k} \qquad (2)$$

The first term in (2a) is the same as in the linearly separable case, and controls the learning capacity, while the second term controls the number of misclassified points. The parameter C is user-defined and can be interpreted as a regularization parameter, because it defines the machine sensibility to the errors: for a small C-value, the optimal hyperplane of separation maximizes the distance of the nearest point of S (the set of points to classify); vice versa, for a big C-value, the hyperplane minimizes the number of points not correctly classified. Where it is not possible to have a hyperplane defined by linear equations on the training data, the techniques described above for linearly separable data can be extended to non-linear decision surfaces. A technique introduced by Boser et al. [5], [6], [7] maps input data from an input space into a high dimensional feature space through some nonlinear mapping, by using a specific kernel function *K* (equation 3), such that:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \qquad (3)$$

where $\phi(\mathbf{x})$ is the mapping into feature space ok $\mathbf{x}$ input data vector. Details of some kernel functions and their parameters used with SVM classifiers are discussed by Vapnik [12].

### 3.1 Building a SVM classifier

Balancing reliability and computational complexity of kernels, we analyzed the performances of SVMs using a polynomial kernel, since it allowed to obtain noteworthy performances with a low computational load and small training and simulation times; it has the following equation:

$$K(x_i, x_j) = (\gamma \|x_i - x_j\| + \mu)^{\lambda}, \gamma > 0 \qquad (5)$$

Considering (5), more than C, we had to set a group of parameters admitting real positive values. This setting procedure is necessary to obtain a Confusion Matrix (CM) which evaluates the goodness of a trained classifier. In this phase, CM has to be obtained by using training database (in our case DBTrain) and has to be as similar as possible with a square unitary matrix. In fact the element xij of confusion matrix is the probability P that a single pattern belonging to the ith class could be classified as belonging to the jth class. For our case of study, the CM has the following template:

$$\begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix}$$

In order to explain the setting procedure, let us denote:

- $\nu_k$ as the value of array of various parameters at the kth step of our procedure (k=1,...,N);
- $CM_k$ as the k$^{th}$ Confusion matrix obtained by using the $\nu_k$ array;
- $CM_I$ as the optimal Confusion matrix;
- $\varepsilon$ as an opportune error-threshold ($0<\varepsilon<0.3$).

The upperbound for ε was setted equal to 0.3 because it is a sufficiently small value for treated data, but other values can be considered according to specific application.

The *setting procedure* is described in the following flow chart (Fig. 4).

The best CM has been obtained considering the values λ=7; C=100; γ=1; μ=0. In (6) it is showed this CM:

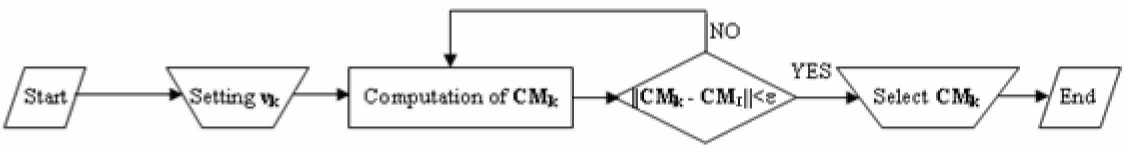
$$CM_{train} = \begin{bmatrix} 0.9566 & 0.0434 \\ 0.0534 & 0.9466 \end{bmatrix} \qquad (6)$$

This CM shows a good performance of SVM-based classifier; at the same time, the difference between $CM_{train}$ and identity matrix can exclude the learning by heart of SVM classifier.

## 4 Data Pre-processing by Using WTs

The design of a SVM classifier can turn out to be useful both as a first guess model and when real time systems are concerned. In order to improve the results, we have carried out a pre-processing based on WTs to emphasize, if any, characteristics of the signals which are able to furnish a more compact codify of the considered signal. WT also guarantees the possibility of not specifying in advance the key signal features and the optimal basis functions needed to project the signal in order to highlight the features. A WT is characterized by two functions: the scaling function $\phi(x) = \sqrt{2}\sum_{k\in Z} h(k)\phi(2x-k)$ and its associated wavelet $\psi(x) = \sqrt{2}\sum_{k\in Z} g(k)\phi(2x-k)$ where *g(k)* is a suitable weighting sequence. The sequence *h(k)* is the so-called refinement filter. The wavelet basis functions are constructed by dyadic dilation (index *j*) and translation (index *k*) of the mother wavelet $\psi_{jk} = 2^{-j/2}\psi(x/2^{-j} - k)$. The sequences *h* and *g* can be selected such that $\{\psi_{jk}\}_{(jk)\in Z^2}$ constitutes an orthonormal basis of $L_2$, the space of finite energy functions. This orthogonality permits the WDCs $d_j(k) = \langle f, \psi_{jk} \rangle$ and the Wavelet Approximation Coefficients (WACs) $c_j(k) = \langle f, \phi_{jk} \rangle$ of any function *f(x)* to be obtained by inner product with the corresponding basis functions. In practice, the decomposition is carried out just over a finite number of scales *J*. WT with a depth *J* is then given by $f(x) = \sum_{j=1}^{J}\sum_{k\in Z} d_j(k)\psi_{jk} + \sum_{k\in Z} c_J(k)\phi_{Jk}$ [8]. To decompose

Fig. 4 – Flow chart of *setting procedure*.



the considered signal |V|, we theoretically chose to apply Daubechies 2b-level 4, since Daubechies 2 allows to use an adequate compact-support trasform and level 4 allows a good multiresolution analysis, without complications of system and computational load increases. Each signal was divided in four parts (D1, D2, D3, D4): only one of them evidences the defect. Tables 2 and 3 show WDCs (since they are linked to local trend of signal) for jsaem#1 e jsaem#3 (cracks ID, defect on D4), jsaem#6 e jsaem#7 (cracks OD, defect on D1). It can be noticed from Table 2 that WDCs of parts presenting cracks (D4 for jsaem#1 and jsaem#3, D1 for jsaem#6 and jsaem#7) vary at least of one order of magnitude as regards to other parts.

Table 2 – Analysis of WDCs' trend on different parts of the same signal

| Signal | Range WDCs in D1 | Range WDCs in D2 | Range WDCs in D3 | Range WDCs in D4 |
|---|---|---|---|---|
| jsaem#1 | $[-3.2*10^{-4} \div 8.4*10^{-5}]$ | $[-1.1*10^{-4} \div 6.3*10^{-5}]$ | $[-3.4*10^{-5} \div 5.6*10^{-5}]$ | $[-7.3*10^{-4} \div 1.3*10^{-3}]$ |
| jsaem#3 | $[-1.2*10^{-5} \div 5.4*10^{-5}]$ | $[-4.1*10^{-5} \div 1.9*10^{-5}]$ | $[-2.6*10^{-5} \div 2.0*10^{-5}]$ | $[-2.3*10^{-4} \div 2.8*10^{-4}]$ |
| jsaem#6 | $[-2.4*10^{-4} \div 3.3*10^{-4}]$ | $[-1.6*10^{-5} \div 3.0*10^{-5}]$ | $[-3.1*10^{-5} \div 1.9*10^{-5}]$ | $[-1.4*10^{-5} \div 3.3*10^{-5}]$ |
| jsaem#7 | $[-9.0*10^{-4} \div 1.1*10^{-3}]$ | $[-2.6*10^{-5} \div 1.2*10^{-5}]$ | $[-5.2*10^{-5} \div 4.0*10^{-5}]$ | $[-1.8*10^{-4} \div 3.3*10^{-4}]$ |

At the same time, Table 3 shows that WDCs extracted from signals' portions presenting crack at different depths are also different. Because of these conditions, we chose to use also WCDs to realize SVM. 40 patterns (DBTrain) have been used to train the SVM, and the remaining 8 patterns (DBTest) have been used for test phase by means of CM.

Table 3 – Comparative analysis of WDCs on signals' parts showing crack presence

| Signal | Crack Depth | Crack segment | WDCs |
|---|---|---|---|
| jsaem#1 | 20%÷60% (ID) | D4 | $[-7.3*10^{-4} \div 1.3*10^{-3}]$ |
| jsaem#3 | 40%÷100% (ID) | D4 | $[-2.3*10^{-4} \div 2.8*10^{-4}]$ |
| jsaem#6 | 60%÷20% (OD) | D1 | $[-2.4*10^{-4} \div 3.3*10^{-4}]$ |
| jsaem#7 | 100%÷40% (OD) | D1 | $[-9.0*10^{-4} \div 1.1*10^{-3}]$ |

# 5 Classification of data: the SVM approach

Traditional classification algorithms usually univocally define a defect to a given depth. This depth can be thought as a class (category) of defects. A defect can not belong to more than a class at the same time. These kind of mutually exclusive representations are called "crisp". Fuzzy sets theory meets this requirement, since it allows a defect to belong to different classes (depths) at the same time, according to the concept of partial membership [9]. In this section of the paper, we classify defects by means of SVM approach. In particular, a polynomial SVM have been trained by using DBTest. Table 4 shows the classification of 8 patterns of DBTest; 5 pattern of them were wrongly classified (RMSE=62.5%). We suppose that it is due to location of cracks inside the transition region [40%÷60%].

Table 4 – Simulation of classification on DBTest

| Signal | Real classification | Simulated classification |
|---|---|---|
| jsaem#41 | 1 | 1 |
| jsaem#42 | 1 | 2 |
| jsaem#43 | 2 | 2 |
| jsaem#44 | 1 | 2 |
| jsaem#45 | 2 | 1 |
| jsaem#46 | 2 | 1 |
| jsaem#47 | 1 | 1 |
| jsaem#48 | 2 | 1 |

In order to confirm that hypothesis, we analyze the CM (so-called CM') computed by means of misclassified signals (see (7)) which values are close to 0.5.

$$CM' = \begin{bmatrix} 0.526 & 0.474 \\ 0.512 & 0.488 \end{bmatrix} \quad (7)$$

In addition, CM' retrieves a sort of indication about the membership of the whole set of misclassified signals to the transition zone. Due to the fact that the elements of CM' are nest to 0.5, we can approximate the information carried out by CM' on the whole set of misclassified signals to each element of the same set. So, each element of the set of misclassified signals belongs to the transition zone ([40%÷60%]). With respect to Fuzzy approach, which uses a classification procedure composed by three steps (Fuzzy Inference, Fuzzy Entropy and Subsethood Operator) [9], the approach exploiting SVM is characterized by a simpler classification structure. In particular, just two steps (SVM-based classifier & CM) are needed. The proposed approach allows to classify cracks in smaller and separated intervals of deepness, with high performances and reduced computational load, this way avoiding the presence of indecision regions.

# 6 Conclusions

In this paper a novel approach to classify defects in metallic plates in terms of their depth starting from a set of experimental measurements is proposed. Particularly, SVMs and CMs have been taken into account to solve the problem of "multi-membership" of defects to several categories. A pre-processing phase has been carried out by means of WTs, with the extraction of features related to local trends of the signals. In classification phase, an hybrid system based on polynomial SVM and CM (with its improved modification CM') has been used in order to determine the defect's depth and quickly classify the results with low-computational complexity algorithms. A classification has been carried out on three depth ranges ([20%÷40%], [40%÷60%] e [60%÷100%]), therefore extending the scientific applications of the Fluxset device. Table 5 shows the depth of each crack for DBTest data as retrieved by the hybrid method proposed.

Table 5– Crack depths of DBTest

| Signal | Depth | Signal | Depth |
|---|---|---|---|
| jsaem#41 | [20%÷40%] | Jsaem#42 | [40%÷60%] |
| jsaem#43 | [60%÷100%] | Jsaem#44 | [40%÷60%] |
| jsaem#45 | [40%÷60%] | Jsaem#46 | [40%÷60%] |
| jsaem#47 | [20%÷40%] | Jsaem#48 | [40%÷60%] |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