Assessing Metal Plate Thickness: an SVM Approach with Electromagnetic Methods

Helena G. Ramos, Tiago Rocha, Jakub Král, Dário Pasadas, Artur L. Ribeiro

Instituto de Telecomunicações, Instituto Superior Técnico,
Universidade Técnica de Lisboa, Lisbon, Portugal, hgramos@ist.utl.pt

***Abstract*-**Eddy current testing (ECT) is a non destructive technique that can be used in the measurement of conductive material thickness. In this work ECT and a machine learning algorithm (support vector machine - SVM) are used to classify the thicknesses of three different types of conductive plates. Eddy currents are induced by imposing a voltage step in an excitation coil, while a giant magnetoresistor (GMR) magnetic sensor measures the transitory magnetic field intensity in the sample vicinity. An experimental validation procedure, including machine training with linear and exponential kernels and classification errors, was made for each metal type with sets of sample thicknesses up to 7.5 mm.

I. Introduction

Eddy Current Testing (ECT) is a widely used technique in Nondestrucive Testing (NDT) to detect and characterize defects in metallic materials [1-3]. Traditional EDT uses sinusoidal excitation signals but, more recently, transient eddy currents (TEC) produced by a square wave, received interest in several applications such as the detection of defects [4,5], the characterization of sub-surface cracks [6,7] or thickness measurement [7-9]. Due to the rich frequency content of the signal used deeper penetration of the electromagnetic field on the sample is achieved and simultaneous evaluation of the material at different depths can be carried out.
The authors of this paper have previously successfully implemented measurement systems either using harmonic or transitory eddy current techniques with GMR sensors to determine plate thickness [8-11]. The present paper reports the implementation of a support vector machine (SVM) algorithm to the TEC raw experimental data obtained with a GMR sensor when plates having unknown thicknesses are being tested.
SVM is a tool capable of recognizing patters, used in regression analysis and classification [12]. The application of a transformation kernel to the input data is often beneficial [13]. It has been applied in ultrasonics NDT to classify planar and volumic defects [14]. Defect characterization has also been done resorting to ECT and SVM, determining the depth [15] and shape [16] of a defect.
The objective of this work is to classify the thickness of conductive plates using ECT and SVM in order to predict more accurate values.

The rest of this paper is organised as follows. In Section II the setup implemented to acquire the experimental database and the available metallic samples are described. In Section III the feature extraction and the SVM based thickness classification are introduced. Next, the proposed method is carried out to determine the thickness of the plates. The last Section is the conclusion and futher work is proposed.

II. ECT Method and Experimental Setup

The experimental setup, depicted in Fig. 1, includes the eddy current testing (ECT) probe with an instrumentation amplifier, a step generator, a data acquisition board (DAQ) and a personal computer.

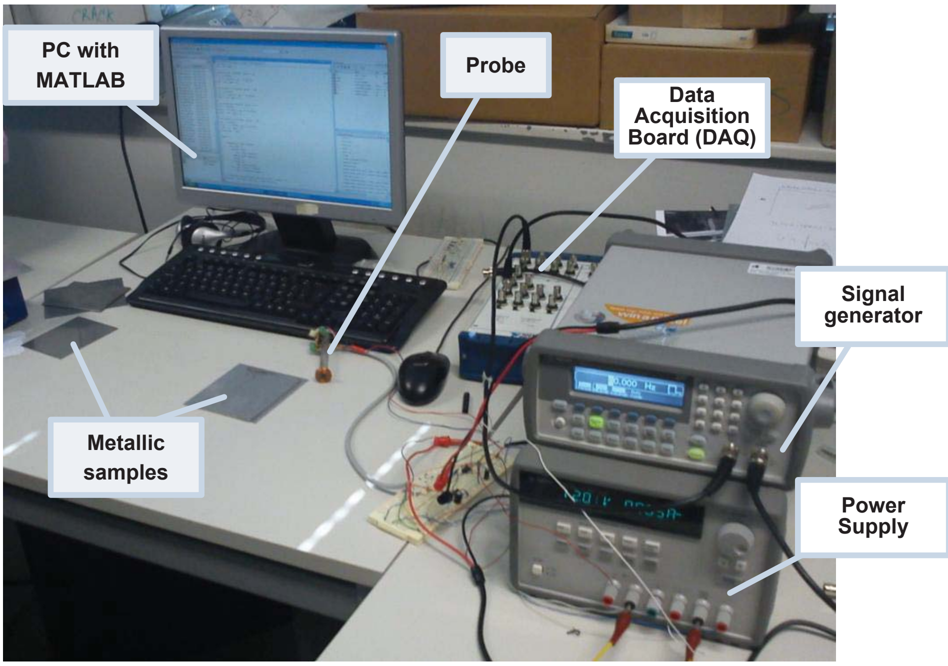

Figure 1. Experimental setup.

The method used to obtain the experimental dataset to compute the plate thickness uses a probe to induce eddy currents on the sample material and to measure the magnetic field. The probe, depicted in Fig. 2, includes an excitation coil with 100 turns and a GMR sensor (AA002-02 from Non Volatile Electronics - NVE). A voltage step is imposed in the excitation coil while the GMR measures the transient of the magnetic field resulting from the current pulse that runs in the excitation coil and the eddy currents induced in the sample plate.

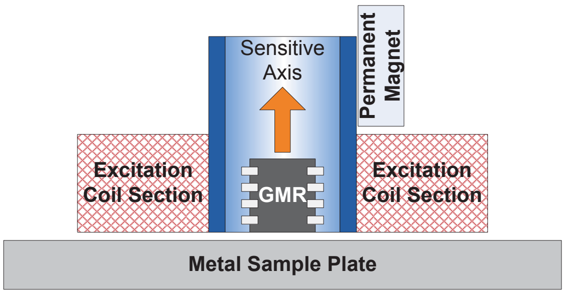

Figure 2. Probe with excitation coil, GMR, permanent magnet and sample plate.

The magnetic sensor includes four GMRs assembled in a Wheatstone bridge configuration and has linear sensibility in a wide range of frequencies (direct current to 1 MHz) if properly polarized with an external constant magnetic field obtained from a permanent magnet carefully placed in the probe structure as depicted in Fig. 2. The magnetic sensor sensitive axis is perpendicular to the plate so that the sensor picks up both magnetic fields that carry thickness information: the primary magnetic field (resulting directly from the current that runs in the excitation coil) and the opposing field generated from the induced eddy currents that run in the plate.
The step generator is composed by an arbitrary waveform generator (Agilent 33220A), a power supply and a MOSFET (NIF9N05). The waveform generator delivers to the MOSFET gate a square wave with a period that lasts for a time long enough to allow the transient signal to reach steady state (larger than 10 ms). A power supply of 6V is connected to the coil and with MOSFET acting as a switch, the voltage is periodically applied to the excitation coil. The MOSFET switches on/off the current in the excitation coil.
The DAQ is triggered by the positive transition of the step generator output voltage and acquires samples at a sample rate equal to 1.25 MS/s. The personal computer runs an application in Matlab that processes the acquired signal, extracts the signal features, trains and tests the machine learning algorithm.
The sample plates used are made from three different metal alloys: aluminum 1050, aluminum 3105 and stainless steel Inox 304. These plates have no arbitrary thickness. The only plates available had a minimum

thickness of 0.5 mm and maximum of 3 mm (depending on the material) with usually 0.5 mm step (0.5, 1.0, 1.5, 2.0 mm). Hence to simulate larger thicknesses, a bundle of plates were stacked and several measures were taken for the same thickness with all the plate permutations possible. To reduce the liftoff effect [17] caused by incorrect probe positioning, the probe was slightly moved above the stack bundle every 10 measures, and a total of 50 measures per plate permutation was made.

The total thicknesses measured for each metal type were:

- Inox 305: 0.5 to 3.5 mm, 0.5 mm steps.
- Aluminium 1050: 1 to 5 mm, 1 mm steps.
- Aluminium 3105: 1 to 7.5 mm, 0.5 mm steps.

III. Signal Processing and Feature Extraction

The step generator impose an exponential current wave to the probe. The duration of the pulse active state and the data acquisition last long enough so that the transient response on the GMR sensing element reaches steady state. The whole the transient is acquired by the data acquisition board. An example of two transient curves obtained for the same plate is depicted below. A slight difference in the direct current (DC) component is evident due to the small movements made by the user during tests. To ignore these DC changes the signal was inverted and it was assumed that the exponential always tends to the value zero.

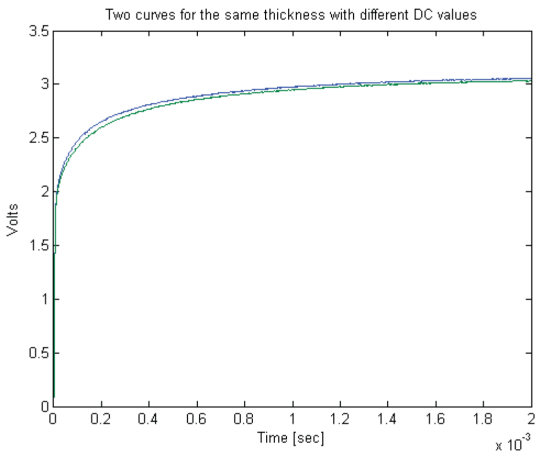

Figure 3. Output voltage of the GMR sensor for two measures concerning the same plate.

Signal processing is required to optimize the machine learning training and classification. The signal processing consists in the inversion of the signal, removal of the DC component and waveform normalization. Fig. 4 depicts examples of processed waveforms for several thicknesses of Inox 304 material.

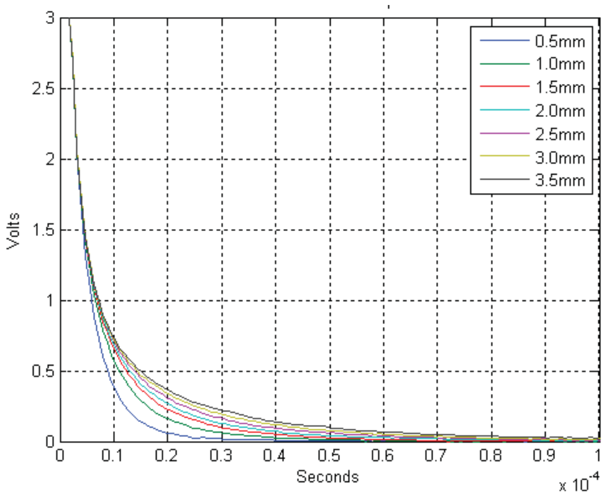

Figure 4. Examples of processed transitory waveforms for all the thicknesses of the Inox 304 material.

The chosen features used to train the SVM are the waveform itself (2500 values), the first four values of the curve's autoregressive (AR) model, the first five discrete cosine transform (DCT) elements and the sum of all the elements of the waveform. This gives a total of 2510 features per measurement.
A classification model was chosen instead of a regression model because of the limited number of plate thicknesses available and the accuracy limitation due to the error introduced by stacking plates to simulate larger thicknesses.

IV. Experimental Validation

It was initially defined that 70% of the samples would be used to train the SVM, while the remaining samples would be used to validate the model, by comparing the obtained SVM classifications against the corresponding sample thicknesses. Five-fold cross-validation was implemented to avoid over fitting. Both linear and exponential kernels were tested. The software used in this work was Matlab with LIBSVM library [18]. Table 1 shows the accuracy of the thickness classification.

Accuracy	Linear kernel [%]	Exponential kernel [%]
Inox 304	100.00	100.00
Al 1050	100.00	100.00
Al 3105	98.48	99.64

Table 1. SVM classification accuracies for each metal type and for linear and exponential kernel.

No classification errors were made with Inox 304 and Al 1050 materials (100% accuracy). However, with AL 3105 the best results were obtained with the exponential kernel, using a cost value C=10 and gamma value g=10. These two parameters were obtained after training and testing the SVM with several C and g values and choosing the ones that yielded the best results (99.64% accuracy). Only three out of 960 aluminium 3105 measurements were misclassified, in 3.5, 4.5 and 6.5 mm thicknesses.

V. Conclusions

This experimental work demonstrates the ability to classify metal thickness using ECT and SVM. Features were successfully extracted and used to train a learning machine, achieving classification errors lower than 1.52%. As future work it would be relevant to also use support vector regression models (SVR) to accurately measure the thickness of a known metal material.

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