Metal Plate Thickness Classification In Eddy Current Testing Using Support Vector Machine

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***Abstract*-**Eddy current testing (ECT) is a non destructive technique that can be used in the measurement of conductive material thickness. In this work a machine learning algorithm (support vector machine - SVM) is applied to ECT data, obtained for three different types of conductive plates, and classifies their thicknesses. 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 step wave are being tested. These signals have a rich frequency content and deeper penetration of the electromagnetic field on the sample is achieved allowing simultaneous evaluation of the material at different depths to be carried out. Good results have been obtained in several applications such as the detection of defects [4,5], the characterization of sub-surface cracks [6,7] or thickness measurement [7-9].

Previous work using transient and harmonic eddy currents with GMR sensors has been successfully implemented to measure plate thickness [10-11]. The present work implements a support vector machine (SVM) algorithm to the GMR transient output voltage in order to train the SVM and classify metal plates with known thicknesses.

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]. SVM have 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 goal of this work is to classify the thickness of conductive plates using ECT and SVM with minimal error.

The experimental setup used and the explanation of the working method is made in Section II. In Section III the signal processing and the feature extraction applied to the acquired data is described. The experimental results are validated in Section IV, and finally, in Section V the conclusions are stated and future work is suggested.

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 digital acquisition board (DAQ) and a personal computer.

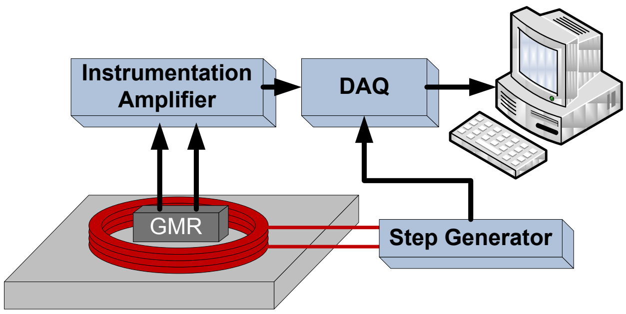

Figure 1. Experimental setup.

This method uses a probe to induce eddy currents on the sample material and to sense the magnetic field generated from these currents. 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 to the excitation coil while the GMR measures the transient magnetic field generated by both excitation coil and eddy currents in the sample plate. The eddy currents induced in the sample material will be affected by the thickness of the plate, thus by analyzing the magnetic field generated by them it is possible to obtain information that is correlated with the plate thickness.

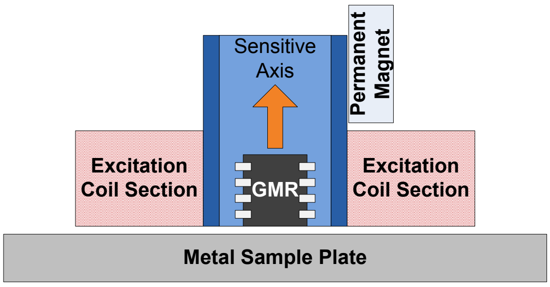

Figure 2. Probe with excitation coil, GMR, permanent magnet and sample plate.

The magnetic sensor includes four GMRs assembled in a Wheatstone bridge and has linear sensibility in a wide range of frequencies (direct current to 1 MHz) if properly polarized with an external constant magnetic field. Polarization is made with a permanent magnet carefully placed in the probe structure. The magnetic sensitive axis is perpendicular to the plate so that the sensor picks up both magnetic fields that carry thickness information: the excitation field and the opposing field generated from the induced eddy currents.
The step generator includes an arbitrary waveform generator (Agilent 33220A) and a MOSFET (NIF9N05). The waveform generator outputs a square wave, with a large enough period to allow the transient signal acquisition (larger than 10 ms), to the MOSFET gate so it imposes a voltage step (0 V to 6 V) in the excitation coil without restricting the current.
The DAQ is triggered by the positive transition from the step generator and acquires samples from the GMR output at a rate of 1.25 MS/s. It acquires enough samples to allow the capture of the transient curve of the magnetic field as well as the steady state curve. The personal computer runs a developed program 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.

Each acquired curve has information regarding the plate thickness. The procedure to evaluate the plate thickness has different steps: prior to train the SVM, a large number of curve samples have to be acquired and the relevant information (features) has to be extracted for each sample and then normalized. After the training the machine is obtained and it can be used to classify any sample presented to it.

III. Signal Processing and Feature Extraction

Feature extraction is required to train the machine and normalization is used to optimize the classification. The signal processing is applied to the raw data obtained from the GMR output and consists in taking the negative of the acquired signal, removing the steady state component, so the waveform always tends to zero. Normalization of the waveform consists in dividing the whole curve by the maximum value, so all its components are between 0 and 1. Fig. 3 depicts the raw data of two acquisitions made for the same thickness. A small difference in the offset value can be seen, and it is caused by a slight change in the lift-off of the probe.

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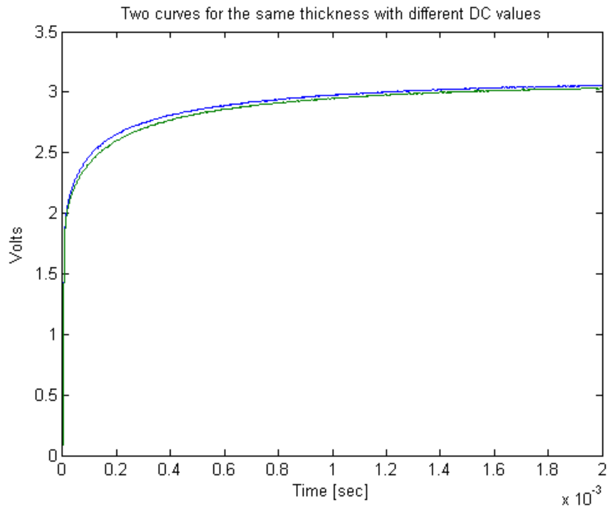


Figure 3. Example of two transitory waveforms for the same thicknesses of the Inox 304 material.

Fig. 4 depicts examples of waveforms after signal processing for several thicknesses of Inox 304 material.

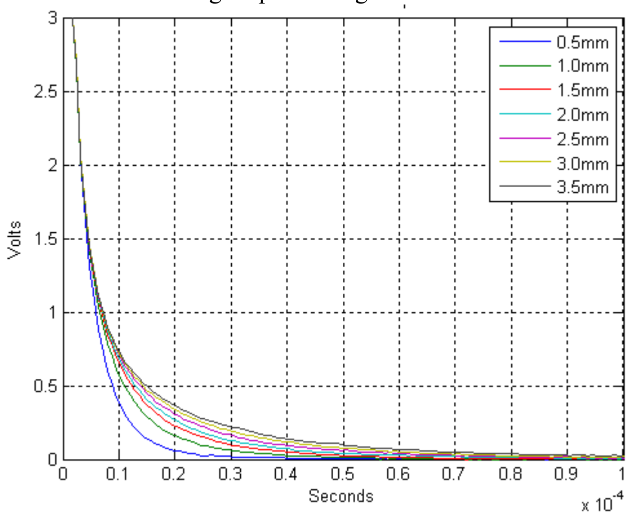
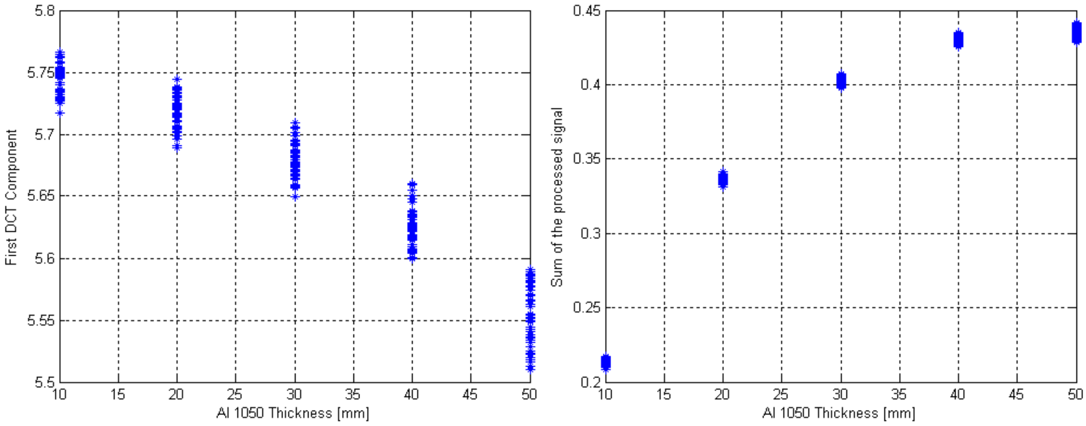


Figure 4. Examples of processed transitory waveforms for all the thicknesses of the Inox 304 material.

Observing the transient curves in Fig. 4 it is visible that the rate of exponential cadence differs according to the thickness. A simple feature that can be used is the total sum of all the elements of the curve, however many other features can be extracted. Initially an iterative least squares exponential fitting was tested for each curve, but it too time-consuming and not practical considering the number of samples, hence the chosen features had to be elements of a model capable of partially reconstructing the curve and also fast. These were 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.

Two examples of features extracted with relevant information are depicted in Fig. 5, where the first DCT coefficient (a) and the sum of all the points of the curve (b) are depicted.



(a) (b)

Figure 5. Examples of features extracted from the acquired curves of Aluminium 1050. (a) First DCT coefficient; (b) Sum of all the curve points.

Observing Fig. 5 it is visible that is it almost trivial to manually define threshold values to the sum results that define an area where each thickness classification is made, however this is exponentially less accurate when the thickness increases. The first DCT coefficient is a feature that, in this particular case, helps to classify the larger thicknesses, but it is not so accurate for thinner plates. This example is applied for the Aluminium 1050, but it may not be the same case for Inox 304 or Aluminium 3105, where other features can be more useful for the SVM classification.

IV. Experimental Validation

A relatively large number of samples (a minimum of 50 samples per thickness) were acquired to reduce the classification error. It was initially defined that a randomly selected 70% of the samples would be used to train the SVM, while the remaining samples would be used to validate the model, by observing the misclassifications by the obtained SVM against the corresponding sample thicknesses. Five-fold cross-validation was implemented to avoid over fitting the training machine. Both linear and exponential kernels were tested. The software used in this work was Matlab with LIBSVM library [18].
To obtain the best parameters, a parameter sweep was made for linear kernel (C parameter) and exponential kernel (C and g parameters). Table 1 shows the best accuracies of the thickness classification of the remaining 30% of the samples.

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%. The exponential kernel showed better results than the linear and it is probably due to the exponential nature of the problem. The maximum thickness measured (7 mm) has surpassed the initial expectations. As future work it would be relevant to further explore more features to extract. Also the use of support vector regression models (SVR) could be implemented to accurately measure the thickness of a known metal material.

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