Fuzzy approach and Eddy currents NDT/NDE devices in industrial applications

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In this Letter, detection/classification of defects are treated in a fuzzy way considering classes of defects to a certain depth characterized by typical ranges of fuzzy similarities. So, depth evaluation is translated in terms of comparison of similarities among signals with defectiveness located at unknown depth and the class of signals without defects. In addition, an FPGA-based board implementing the designed procedure will be discussed. The performance gives the comparability of the results with other established techniques.

Introduction: During the life cycle of a manufacturing, mechanical loads could reduce the quality of the material compromising its integrity/functionality from which it is imperative the exploitation of integrity tests [1, 2] such as NDT/NDE based on Eddy currents (ECs). To distinguish defectiveness to different depths it is not possible by means of visual inspection of signals because different depths produce signals too similar among them. Specifically, an EC mono-dimensional signal presents a typical deflection next to the defect according on its depth so that the presence of a defect to a certain depth, in this Letter, is detected in terms of reduction of its *similarity*, on one hand, with respect to classes of signals with known defects and, on the other hand, with a class of signals without defects. Grouping in different classes the signals with defectiveness at different depths and in a single class all of signals without defects, each of above-mentioned classes is characterised by particular range of similarity, so that depth evaluation will take place by comparison of similarities among the representing signal with respect to each class. In the past, statistical, neural and tomographical approaches have been tuned-up to solve the problem at hand [3–6]. Good results have been carried out in [7] in which the problem was solved by heuristic techniques and in [4] where a statistical approach based on principal components analysis reduced the problem dimension by an excessive increment of computational complexity without appraisable advantages in terms of performance. Unfortunately, sampling techniques produce noises so that it appears natural to formulate the problem in a fuzzy way by techniques based on fuzzy similarities (FSs) classifying, on one hand, by a reduced computational complexity procedure and, on the other hand, solves doubtful cases in terms of presence/absence of defectiveness. Next sections describe FS approach for our purpose. Then, principal characteristics of the experimental database are reported. Finally, hardware implementation, results and comparisons with wavelet/neural techniques jointed to the main conclusions are drawn.

FS concept: mathematical aspects for classifying defectiveness: A fuzzy set A is defined by a membership function, $\mu_A(\cdot): A \to [0,\ 1]$, or thinking A as a point in a certain metric space: distance between two fuzzy sets A and B, $d(A, B)$, is equivalent to the distance between two points in an n-dimensional space. If A represents a signal with defect and B a signal without defect, $d(A, B)$ measures how much the signal with defect is next to that one without defects. Since similar defects generate similar signals, we group the signals into classes of defectiveness converging into a single fuzzy set which represents the class with that defectiveness. In addition, if B is the fuzzy set representing the class of signals without defects, then $d(A, B)$ indicates how much the class A is next (in a fuzzy sense) to the class B. In particular, the presence of a defect in a signal is assessed by reduction of its FS, as a metric, with the class B of signals without defects. Formally, on the set of all fuzzy sets, $F(X)$, we define the normalised function FS: $F(X) \times F(X) \to [0,\ 1]$ such as for $A, B, C \in F(X)$: (i) $S(A,\ B) = S(B,\ A)$ (to guarantee symmetry); (ii) if $A \subset B \subset C$, then $S(A,\ B) \geq S(A,\ C)$ and $S(B,\ C) \geq S(A,\ C)$ (to guarantee monotonicity); and (iii) $S(A,\ A) = 1$ (to guarantee reflexivity). If no-defectiveness (ND) is the class of signals without defects and kind of defectiveness (KD) is the generic class of signals with known defects, FS of an unknown signal Y (with unknown defect) with respect to ND or KD, FS(ND/KD, Y), takes place by an FS with the properties above defined. In this Letter, after verification of the fuzziness of the classes of signals by entropic indexes such as linear index (LI) and fuzzy entropic (FE) index computed as $\mathrm{LI} = (2/n)\sum_{i=1}^{n} \min(\mu_{\mathrm{ND/KD}}(\cdot)(1 - \mu_{\mathrm{ND/KD}}(\cdot)))$ and $\mathrm{FE} = (1/n)\sum_{i=1}^{n} \min(-\mu_{\mathrm{ND/KD}} \log(\mu_{\mathrm{ND/KD}}(\cdot)) - (1 - \mu_{\mathrm{ND/KD}}(\cdot))\log(1 - \mu_{\mathrm{ND/KD}}(\cdot)))$ and taking into account that high values of LI and FE are indicative of fuzziness of the class of signals, the author exploited four different FSs formulations [7] $\mathrm{FS}_1(\mathrm{ND/KD}, Y) = (1/n)\sum_{i=1}^{n}(\min(\mu_{\mathrm{ND/KD}}(\cdot) - \mu_Y(\cdot)))/(\max(\mu_{\mathrm{ND/KD}}(\cdot) - \mu_Y(\cdot)))$; $\mathrm{FS}_2(\mathrm{ND/KD}, Y) = (1 - ||\mu_{\mathrm{ND/KD}}(\cdot) - \mu_Y(\cdot)||_j)/n$; $\mathrm{FS}_3(\mathrm{ND/KD}, Y) = 1 - \sum_{i=1}^{n}(||\mu_{\mathrm{ND/KD}}(\cdot) - \mu_Y(\cdot)||_j)/(\mu_{\mathrm{ND/KD}}(\cdot) + \mu_Y(\cdot))$ and $\mathrm{FS}_4(\mathrm{ND/KD}, Y) = 1/(1 + ||\mu_{\mathrm{ND/KD}}(\cdot) - \mu_Y(\cdot)||_j)$ where $j \in \{1,\ 2,\ \infty\}$; n is the sampling cardinality; $\mu_{\mathrm{ND/KD}}(\cdot)$ and $\mu_Y(\cdot)$ are membership values related to ND, KD and Y, respectively. Obviously, if Y is a signal without defects, $\mu_Y(x_i) = \mu_{\mathrm{ND}}(x_i) = 1$; otherwise, if it is related to a certain defectiveness KD, then $\mu_Y(x_i) = \mu_{\mathrm{KD}}(x_i) < 1$.

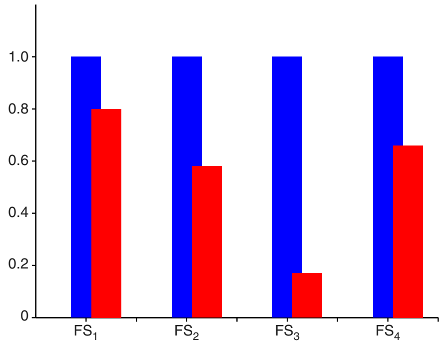

Fig. 1 *FSs for A-ID class (red bars) against benchmarking signals without defects (blue bars)*

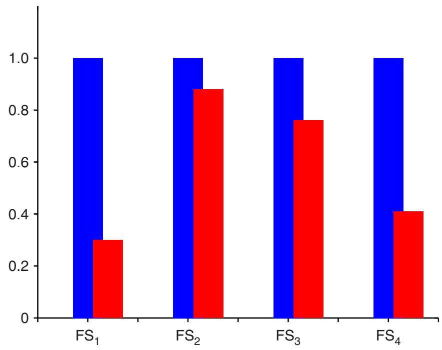

Fig. 2 *FSs for B-ID class (red bars) against benchmarking signals without defects (blue bars)*

Experimental dataset: At our laboratory, plates $140 \times 140 \times 1.25\ \mathrm{mm}^3$ with rectangular defects having depths of 20, 40, 60 and 100% of its thickness was investigated. A fluxset-type probe moved over the specimen by a 0.5 mm-step automatic scanning procedure along x and y axes. A driving signal-triangular shape (125 kHz, 2 V_{pp} amplitude) was applied to saturate the core material inside the probe. An external sinusoidal exciting field (1 kHz, 107 mA) was generated close to the specimen, thus inducing ECs on the surface as well as on subsurface layers. 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. Signals at our disposal were separated into two parts: (i) the training section constituted by 195 signals with inner/outer defectiveness (ID/OD) falling on four classes: A-ID, with 40 signals from 20 to 60% depth (eight signals-depth 20%, eight signals-depth 30%, eight signals-depth 40%, eight signals-depth 50% and eight signals-depth 60%); B-ID, with 50 signals from 40 to 100% (ten signals-depth 40%, ten signals-depth 50%, ten signals-depth 60%, ten signals-depth 80% and ten signals-depth 100%); C-OD, with 60 signals from 60 to 20% (12 signals-depth 20%, 12 signals-depth 30%, 12 signals-depth 40%, 12 signals-depth 50% and 12 signals-depth 60%); D-OD, with 45 signals from 100 to 40% (nine signal-depth 40%, nine signals-depth 50%, nine signals-depth 60%, nine signals-depth 80% and nine signals-depth 100%); (ii) the testing section constituted by 100 signals ID/OD falling on four classes with known depths but, for our purposes, considered as unknown (A-ID)*, (B-ID)*, (C-OD)* and (D-OD)* (25 signals per class). Finally, a class with signals without defects has been made, ND, with 45 signals.

Some statistical considerations and results of interest: EC signals histograms present Gaussian trends so that each class of signals can be represented by a single membership function, $\mu_{ND}(\cdot)$ or $\mu_{KD}(\cdot)$, whose means and standard deviations are representative of all signals afferent to each class. Since different signals belonging to the same class present light variations of mean and standard deviation, $\mu_{ND/KD}(\cdot)$ have been made as $\mathrm{mean}_{KD/ND}$ = *the mean value of all the means* and $\sigma_{KD/ND}$ = *the maximum value of all the standard deviations* covering the whole cases of signals belonging to each class. To underline the fuzziness of each signal, LI and FE have been computed for each class of signals: high values of them confirmed a high level of fuzziness. The procedure is showed in Figs. 1–5, where the presence of a defect is detected by comparison of the signal with a benchmark signal (without defects): low values of FSs show a strong presence of a defect. In addition, for each class of defect (with respect to the depth), each detection presents ranges of possible values of FSs and, by comparison, the depth of the defect can be carried out.

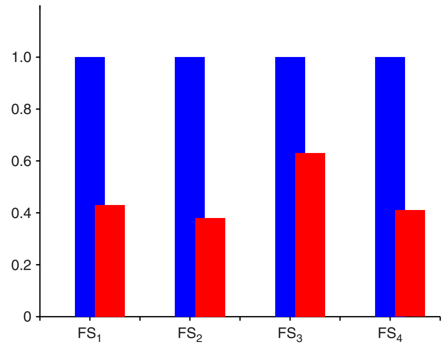

Fig. 3 *FSs for C-OD class (red bars) against benchmarking signals without defects (blue bars)*

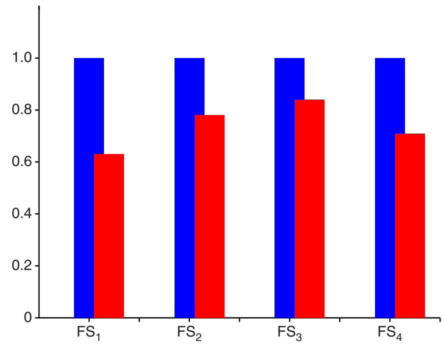

Fig. 4 *FSs for D-OD class (red bars) against benchmarking signals without defects (blue bars)*

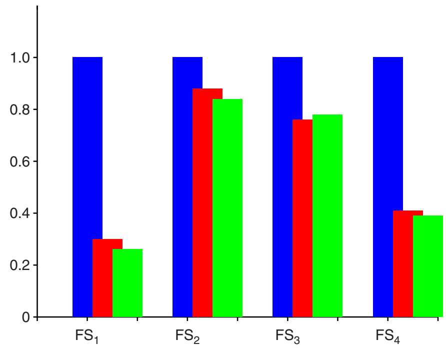

Fig. 5 *Unknown signal classified as B-ID (green bars) against benchmarking signals without defects (blue bars)*

Field Programmable Gate Array (FPGA) fuzzy-based classifier: the hardware implementation: Here, an FPGA device Xilinx Virtex-II pro device was exploited and mounted on a board including: (i) rs232 serial communication port as peripherals for interfacing the board with a personal computer (PC) or other external acquisition devices; (ii) an liquid crystal display (LCD) to get facilities on visual informations; (iii) a random access memory used as a data buffer; and (iv) a set of light-emitting diodes and programmable switches. The acquisition of signals can be made directly from the fluxset probe and the classification is operated by FPGA device answering by visualisation on the LCD display. An objected programming language such as C was exploited for implementing FSs to create a simple system because just Gaussian membership functions and similarities formulas were transferred on hardware. Finally, by means of a decision tree linked to a panel allows us to select the kind of similarity by pushing buttons on the board visualising the results of classification (Fig. 6).

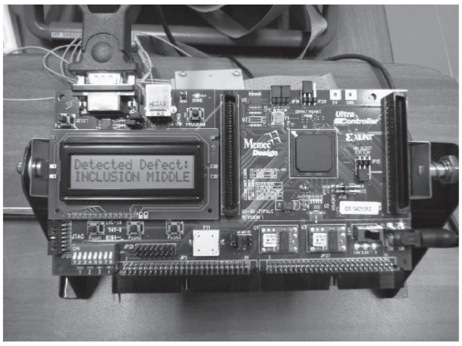

Fig. 6 *FPGA fuzzy-based classifier*

Table 1: Comparison of results with other techniques

Technique	Detection (%)	Classification (%)
FS_1	100	99.52 (ID)–96.98 (OD)
FS_2	100	99.57 (ID)–97.01 (OD)
FS_3	100	99.54 (ID)–96.55 (OD)
FS_4	100	99.53 (ID)–96.73 (OD)
Wavelet coherence/fuzzy clustering	100	99.46 (ID)–96.72 (OD)
Neural networks	100	96.10 (ID)–96.10 (OD)

Conclusions: Starting from ECs signals, four FSs formulations and two indexes of fuzziness have been exploited to design a procedure to detect and classify defectiveness. All defects have been detected and, in terms of depth, the system has correctly recognised over than 99% for ID defects and around 97% for OD ones (Table 1). Finally, the reduced computational load of the proposed procedure is definitely attractive for real-time application and/or hardware implementation. Finally, a comparison with other established technique was performed carrying out comparable results but exploiting a lower computational complexity suitable for hardware design useful for real-time requirements.

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One or more of the Figures in this Letter are available in colour online.

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