ECT-DATA FUSION BY THE INDEPENDENT COMPONENT ANALYSIS FOR NON-DESTRUCTIVE EVALUATION OF METALLIC SLABS

Simone Fiori and Pietro Burrascano

DIE–UNIPG, University of Perugia, Italy
E-MAIL: SFR@UNIPG.IT

ABSTRACT

The aim of this paper is to present an application of ICA to non-destructive evaluation by unsupervised data-fusion, which aims at discovering the flaws affecting a metallic slab. The signals acquired through an eddy-current probe for non-destructive evaluation purposes are affected by strong noise and disturbances due to the mechanical system that the probe is mounted on. The availability of multiple measurements allows performing a linear data-fusion which returns independent latent signals, one of which represents the flaw-related signal recovered from the noisy mixture. A one-unit neural ICA system is employed to extract such latent signal.

1. INTRODUCTION

Real-world measured signals consist almost invariably of data carrying information buried by noise and disturbances originated from the environment and from the measurement system itself. When the noise is strong, i.e. the signal-to-noise ratio is low, often it is necessary to perform some kind of pre-processing in order to emphasize the information content of the data. One among such techniques is data-fusion: It consists in the combination of multiple (redundant) observations of the same phenomena, often conducted through different kinds of sensors; a proper combination of such large amount of data may allow suppressing the unwanted disturbances and to extract the meaningful signals.

A relevant industrial problem where data-fusion might prove useful is non-destructive evaluation (NDE) of metallic slabs by eddy-current testing (ECT). The ECT [5, 6] is a non-destructive evaluation technique especially well suited for metallic object inspection by a probe system.

In ECT-NDE, an electromagnetic probe is slid over a conductive object. The exciter coil is driven with medium-range frequency (< 100kHz) stabilized sinusoidal current producing a magnetic field, which induces eddy currents in the object surface near the exciter. These currents produce their own magnetic fields, which are always in opposition to the exciter field; a part of the eddy currents experiences conductive losses, therefore these counter fields do not fully balance the exciting field. This phenomenon may be equivalently thought of as the interrogating magnetic field which is back-scattered by the inner layers of the objects [11, 27]. At the level of the coil, the back-scattering phenomenon results in the probe's electrical impedance change, which consists of an equivalent resistance, accounting for the energy loss in the metal, and an equivalent reactive part, which accounts for the phase delay in the scattered field. The differential impedance is sensitive to anomalies or perturbations in the volume in the path of the interrogating magnetic field, such as metal loss, cracks, corrosion or wall thinning.

When a defect is present on the surface of the specimen, to prevent the evolution of the damage, it is important to detect, localize and size the crack; however, the eddy current measurement is corrupted by the skin effect, the lift-off noise and uncorrelated noise. Prior to develop a flaw detection/recognition system, each measurement has thus to be restored, by separately featuring the lift-off signal and the defect signal. The magnitude and the phase of the ECT signals, acquired on the upper and lower sides of the specimen, have been considered as available measures. In order to extract information from the measured data, a proper signal processing algorithm should be designed.

An ECT-NDE data processing approach is proposed in this paper to remove the effects of the eddy-current sensor drift during the horizontal/vertical scanning of an inspected metallic slab. Neural techniques have recently been applied to the solution of electromagnetic problems (see e.g. [3, 8, 26, 27] and references therein), and it has been especially proven, by recent experimental research works, that the use of ICA enables us to acquire additional knowledge from measurements [10, 25, 28]. (For further reading, a recent survey of successful industrial applications of independent component analysis and blind source separation may be found in [13].)

As an ICA-engine, we use here a one-unit neural system based on 'rigid-body' learning theory. It was introduced in [15] as a new class of learning rules for linear as well as non-linear neural layers, arising from the dynamics of rigid bodies; its usefulness in solving some orthonormal problems has been recently proven, like in optimal data representation by second-order statistics decomposition. Later on, we observed that the mentioned class of learning algorithms is a subset of a larger family of adaptation rules and proposed a general theoretical framework which explains many contributions found in the scientific literature; the general theory, termed *Stiefel-Grassman flow learning*, was presented in [16]. The main idea behind these contributions is to exploit the mathematical knowledge of the algebraic structure of the spaces that the networks' parameters belong to, through the basic instruments provided by differential geometry, as recently suggested for instance in [2, 7, 14, 22], among others; our work also found its roots in some impressive papers on second-order optimization techniques (see e.g. [1, 24]) exploiting physical parallelisms.

As mentioned, the mechanical learning paradigm arises from the equations describing the dynamics of an abstract rigid body, embedded in a force field, which is formed by unitary-mass point-particles positioned over mutually orthogonal axes at unitary distance from axes' origin. For a one-unit network ($m = 1$), the learning equations read:

$$\dot{\mathbf{w}} = \mathbf{A}\mathbf{w},\ \mathbf{p} = -\mu\mathbf{A}\mathbf{w}\ ,\ \mathbf{f} = -2\nabla_{\mathbf{w}}U\ , \quad (1)$$

$$\dot{\mathbf{A}} = \frac{1}{4}[(\mathbf{f}+\mathbf{p})\mathbf{w}^T - \mathbf{w}(\mathbf{f}+\mathbf{p})^T]\ , \quad (2)$$

where $U(\mathbf{w})$ is the system's potential energy function which drives the system dynamics and describes neuron's task. The equations try to learn the weight-vector $\mathbf{w}$ that *minimizes* the potential energy function.

2. APPLICATION TO INDEPENDENT COMPONENT ANALYSIS

The independent component analysis (ICA) aims at extracting independent signals from their linear mixtures or to extract independent features (as latent variables) from signals having complex structure [4, 9, 12, 19, 20, 17].

A way to define the independent components is to employ the maximum or minimum kurtosis principle: Under some conditions, the output of a linear neuron with multiple inputs $\mathbf{x}(t)$ described by $y(t) = \mathbf{w}^T(t)\mathbf{x}(t)$ contains an independent component of the input if the weight-vector $\mathbf{w}$ maximizes or minimizes the fourth moment of neuron response:

$$\mathbf{w}_{\mathrm{ica}} = \arg\max_{\mathbf{w}^T\mathbf{w}=1} \pm E_{\mathbf{x}}[(\mathbf{w}^T\mathbf{x})^4]\ . \quad (3)$$

The observed signal model is $\mathbf{x}(t) = \mathbf{M}\mathbf{s}(t)$, where $\mathbf{s}(t) \in \mathbb{R}^n$ is a vector-signal with statistically independent components, and $\mathbf{M} \in \mathbb{R}^{m\times n}$ is a full-column rank matrix describing the mixing of the independent components into the observable signal or the expected relationship between the latent variables and the observable variables. Apart from special cases, the number of observations m should exceed or equate the number of independent sources n. With the convention that $s_r(t)$ denotes the r^{th} independent component of $\mathbf{s}(t)$, usually the hypotheses made on it are that each s_r is a stationary IID (independent, identically distributed) random signal with zero mean ($E_{\mathbf{s}}[s_r] = 0$), unitary variance ($E_{\mathbf{s}}[s_r^2] = 1$) and is statistically independent of each other at any time. It is also worth recalling that, under the above hypotheses, the *kurtosis* of the signal s_r defines as $\kappa_4^r \stackrel{\mathrm{def}}{=} E_s[s_r^4] - 3$.

In practical situations, it is also common to hypothesize that the signals in $\mathbf{x}(t)$ are mutually uncorrelated, which is equivalent to say that the mixing matrix is orthogonal; without any loss of generality we can suppose $m = n$, thus ultimately $\mathbf{M}^T\mathbf{M} = \mathbf{I}_n$. It is known that when the observable signals are not uncorrelated, a pre-processing stage known as 'whitening' or 'sphering' may be always performed, which has the twofold effect to remove the second-order dependency between the signals and to reduce the number of 'geometrically independent' observations to n (see e.g. [6]).

In the present context, the optimization principle (3) gives rise to the potential energy function:

$$U(\mathbf{w}) \stackrel{\mathrm{def}}{=} \frac{1}{4}\eta\{E_{\mathbf{x}}[(\mathbf{w}^T\mathbf{x})^4] - 3\}\ , \quad (4)$$

with η being a real number allowing to switch between the maximization and minimization problems. The above energy function generates the forcing field:

$$\mathbf{f} = -2\eta E_{\mathbf{x}}[(\mathbf{w}^T\mathbf{x})^3\mathbf{x}]\ . \quad (5)$$

In order to avoid the explicit approximation of the required mean-field, we resort to stochastic optimization, which means dropping down the expectation operator and approximating the average of the stochastic force $\mathbf{f}^\star = -2\eta\mathbf{x}y^3$ with itself.

3. APPLICATION TO NON-DESTRUCTIVE EVALUATION (NDE) PROBLEM

In ECT-NDE, the probe usually consists of a source coil and a pick-up coil connected to a nano-voltmeter. The probe allows for complex-voltage measurements whose change is used for defect detection and identification with particular interest into defect shape.

A typical inspection is carried out in the following way. A conductive specimen is supposed to be affected by a defect located deeply in its volume and thus hidden to the view: A probe is moved on a grid over the specimen accessible surface and a set of differential complex voltage values are thus collected. A strong discontinuity in the homogeneity of the impedance profile in a spatial location clearly evidences the presence of a defect in that zone of the volume; on the basis of this observation, a first automatic screening of the data is performed in order to roughly localize an area of the surface centered around the defect, so that the successive finer analysis is restricted to a narrower specimen volume. As the distribution of the impedance depends on the defect location and shape, it is possible to reconstruct the defect profile by properly treating the measured data [18].

3.1. Experimental set-up

We analyze a set of experimental ECT-NDE data, provided by the Hungarian Academy of Sciences [21]. They have been acquired by a single 'pancake' exciting coil with FLUX-SET sensor (for a detailed explanation of experimental set-up see [21]). The tested specimen consists of a square plate ($8 \times 8 \times 0.125$ cm) of INCONEL material, which presents a rectangular thin crack (about 0.2 mm thick and 9 mm in length), surface (inner defect, ID) or hidden (outer defect, OD) according to the inspection side, located in a region of 2×2 mm width around the plate center. The depth of the defect is about 20% of the plate thickness. The scanned area is a region of 40×40 mm with 0.5 mm spacing along x and y axes; the output voltage is proportional to the absolute value of the y component of the magnetic flux density, and the voltage magnitude and phase have been recorded on a grid of 81×81 measurement points.

Figure 1 represents a real- and imaginary-part pairs among the ECT-NDE signals. Even if the plate has a constant horizontal thickness, the signal has a magnitude related not only to the defect but also to the variable sensor lift-off over the specimen surface, which creates a drift effect on the measurements.

From the experimental set-up, four different measurements are available: The magnitude and the phase of the EC signal acquired from the inner side of plate, and the magnitude and the phase from the outer side of the plate. If a defect is present near one of the surfaces, a measure can be considered as ID and the second one will be OD type. By using a single measurement, the detection of the crack is unfeasible because of two concurring problems:

- When the defect is located near the surface on the same side of the sensor (ID), although the signal-to-noise ratio is high, it does not suffice to provide the detection/recognition system a suitable knowledge to correctly locate and size the flaw;
- When the defect is located on the surface, for OD measurement, the signal related to the crack is completely buried into background disturbance, due to the skin effect, to the lift-off noise and to the uncorrelated Gaussian noise, as can be readily seen from Figure 1.

Our working hypothesis is that the measured signals are linear mixtures of different sources: The signal related to the defect and the one related to the lift-off noise. This suggests

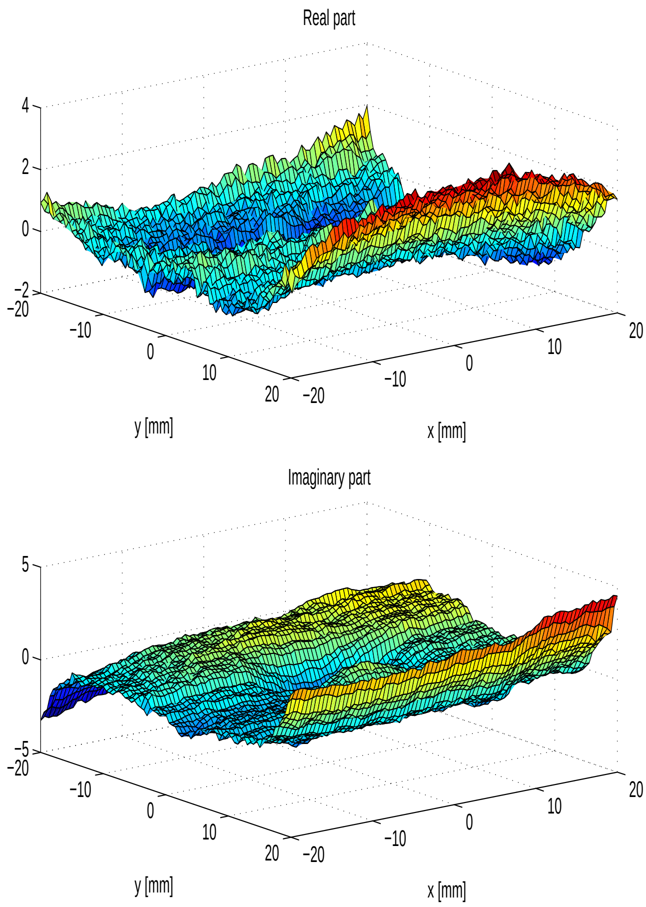

Fig. 1. Real- and imaginary-part of the measured ECT-NDE signal.

that, on the basis of ICA technique, a way can be envisaged to extract the defect signal. More formally, we hypothesize that there exist two latent signals whose linear superposition with proper (unknown) weights give rise to the observed signals. In our model such latent variables are statistically independent, thus they may be separated through an ICA technique.

3.2. Experimental results

As mentioned, we hypothesize a linear model relating the independent signals with the measures. Our proposal for processing the available data is to suppose that the real and imaginary parts of the involved signals interact in an additive way, thus the input signal $\mathbf{x}(t) \in \mathbb{R}^4$ contains 4 scalar sub-signals: the real- and imaginary-parts of both the ID and OD measurements.

The signal $\mathbf{x}$ gets first whitened by mean-value removal and eigenvalue-decomposition based normalization of the covariance matrix, so that the whitened data are centered and have unitary covariance.

As the signal show a non-negligible spatial correlation, the one-unit ICA algorithm is run over $15,000$ samples randomly picked from the set of $81 \times 81 = 6561$ available measures (regardless of their ordering), to simulate stationarity[1].

The algorithm was run with parameters values $\mu = 8$, $\Delta t = 0.001$, $\eta = -0.5$; also $\mathbf{w}(0) \sim \mathcal{N}(0, \mathbf{I}_4)$ (it was then normalized to have unit norm), while $\mathbf{A}(0) = \mathbf{0}_4$.

Figure 2 shows the result of a run: The obtained latent component clearly pertains to the defect signal, which appears no longer buried by lift-off noise. The linear superposition of the measured signals which cancels the background disturbance is non-trivial, as the final neuron weight-vector resulted to be $\mathbf{w} = [-0.2371\ -0.0131\ 0.9072\ -0.3476]^T$.

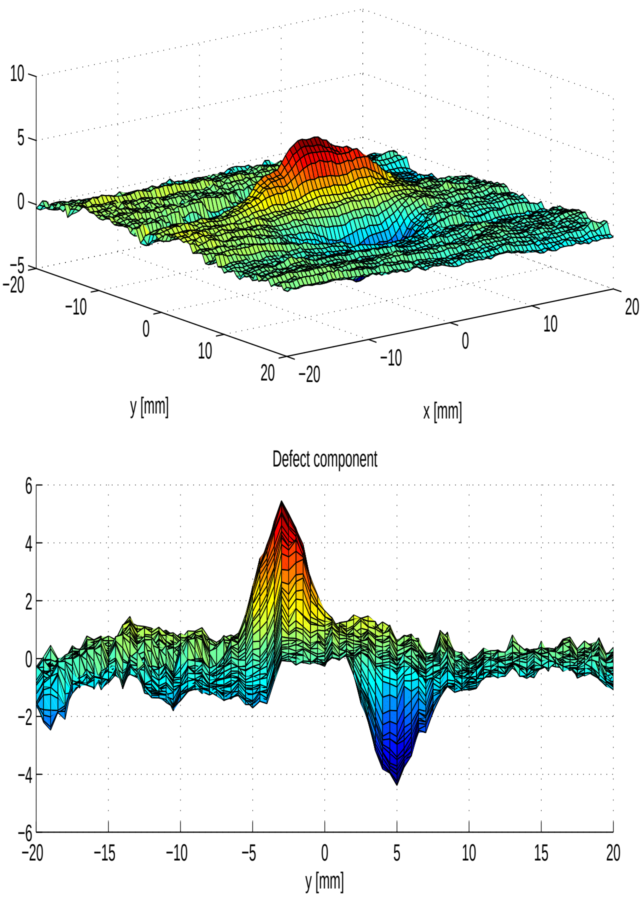

Fig. 2. Estimated latent variable, in the NDE problem, corresponding to the defect signal.

The signal-to-noise (i.e. defect signal to background noise) ratio is good enough to enable an automatic recognition system to locate and describe the crack.

[1]Note that this way of using the signals is data-structure preserving.

4. CONCLUSION AND FURTHER WORK

An engineering problem of industrial interest, the NDE of a metallic slab, has been tackled through a data-fusion technique based on independent component analysis. A real-world case-study, relying on measures provided by the Hungarian Academy of Sciences, has been discussed by analyzing the numerical results obtained by running a one-unit ICA neural system. A thorough formal analysis of the behavior of the 'rigid bodies' learning system is under investigation, as well as a detailed study about the capabilities of ICA-related techniques in non-destructive evaluation tasks.

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