Higher order based image deconvolution in electromagnetic non destructive evaluation of metallic materials

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Abstract. We present a non-destructive magnetic imaging technique developed for the evaluation of hot-rolled stainless steel. Starting from measurements of magnetic field carried out by means of a Hall probe array, magnetic images of sample surfaces are attained. In order to enhance the signal to noise ratio and to detect defects, we have implemented some image processing protocols. In particular we report the contextual application of Independent Component Analysis and Wiener filter to the image deconvolution task focusing on the advantages that such approach assures.

Keywords. Non Destructive Evaluation, Image Processing, Independent Component Analysis.

1. Introduction

In recent years, there has been a significant increase in the use of advanced digital processing techniques due to the substantial benefits that their use entails. In the field of non-destructive inspections, imaging procedures allow to evidence the presence of defects and imperfections in the tested samples in a faster and better way than traditional methods. These tools are commonly applied in radar and ultrasound controls, while they are nowadays focusing the efforts of researchers in the fields of Eddy Current and Magnetic Flux Leakage testing [1,2]. In this framework, we have developed a magnetic imaging technique to perform non-destructive testing of metallic materials. In particular the present method has been designed to detect surface defects in austenitic rolled stainless steel samples. The magnetic images of the sample surfaces are attained in three main steps: a) the samples are locally excited by a suitable static magnetic field; b) the Hall effect sensors measure the magnetic field intensity on a regular grid of positions that covers all the region of interest; c) the overall magnetic images are reconstructed by means of digital processing. In order to test the overall procedure, we have carried out several
experiments by adopting the Hall-probe sensor array depicted in Fig. 1. The main goal of these experiments was the detection of superficial defects consisting of oxide scales, inclusions, marks, and so forth. Due to the requirements of industrial applications, the system has to work in real-time during manufacturing of goods and metallic products. Starting from the first image built up by the measured data, we have applied several filtering and denoising algorithms with the aim of enhancing the image quality in the perspective of a next automatic classification process. In fact, resulting images are substantially the non linear convolution between useful information and the impulsive response of probes, i.e., the signals measured by probes in void. Thus, the filtering action is equivalent to the deconvolution of the measure in void from the useful image. The paper is organized as follows: Section 2 describes the experimental apparatus and the measurement set-up adopted, Section 3 deals about the techniques exploited for the image digital processing focusing on the application of high order statistical analysis to perform image deconvolution while Section 4 reports experimental results with a brief discussion about next developments and critical issues. Eventually we draw some conclusions.

2. Experimental apparatus and measurement set-up

The measurement set-up adopted for inspecting the surface of various samples is summarized in Fig. 1. A prototype array consisting of sixteen linear Hall effect sensors (Allegro A1321) has been realized in our laboratory, see Fig. 2(b). In particular the Hall probes are arranged to return an output voltage signal proportional to the component of the magnetic field orthogonal to the sample surface while the static magnetic field is provided by a U-shape permanent magnet, Fig. 2(a). The austenitic nature of the tested samples assures the linear behaviour of the magnetization respect to the exciting field and the absence of saturation and hysteresis phenomena. In order to reconstruct the images starting from the measurements of $B$ magnetic field carried out by the Hall probes, each of the sixteen output voltage signals go through a passive RC low pass filter and then join into a 16:1 multiplexer that switches periodically between them in order to reduce the number of signal to be acquired from 16 to 1. This goal is achieved by controlling the multiplexer with a 4-bit logical word generated by a digital counter driven by an external clock signal. By varying the clock frequency we are able to vary the sample rate of the single probes. To acquire measurements of the magnetic field over a 2D regular grid of
Figure 2. Prototype array consisting of 16 Hall linear sensors, equipped with passive RC low pass filter, Multiplexer and Digital Counter.

points, the sensor has been connected to a PC controlled X-Y motorized translation stage. The output signal from the multiplexer is acquired by means of an Analog to Digital converter while the Clock signal and the Driving signals of the stepper motors are generated adopting Digital to Analog converters. In particular signal acquisition and clock generation are carried out by a National Instruments USB-6259 device, while the motors controls are supplied by a National Instruments PCI-6711 device. Such devices are programmed by exploiting the National Instruments software LabVIEW. In this way we can define an arbitrary X-Y path for the sensor and simultaneously acquire signals from the array provided by the multiplexer output. For the experiments reported, we chosen to perform several scans along the Y-axis at different X values to obtain images covering a sample area of \(256 \text{mm} \times 250 \text{mm}\) with pixel dimensions of about \(2 \text{mm} \times 0.5 \text{mm}\). For any measurement point we collect the intensity of the magnetic field component perpendicular to the samples surface, as said, then we have for any pixel a scalar quantity, the \(B\)-component. The images reconstructed are therefore analogous to a grayscale image.

3. Image Processing

The samples investigated are made of austenitic stainless steel, i.e. characterized by a high percentage of Austenite, a non-magnetic allotrope of iron. The magnetic field variations induced by the presence of superficial defects are quite low (\(\delta B/B < 10^{-3}\)) thus leading to a voltage signal comparable with the noise introduced by electric devices and by the environment [3,4]. At the same time, hardware processing on the multiplexer output signal is strongly limited since the information content coming from each probe must be preserved. Moreover filtering each probes is quite onerous and with poor scaling properties. It is therefore necessary to perform some digital processing to enhance the signal to noise ratio in order to detect even small defects. Indeed, the magnetic images obtained directly from the measured data exhibit three major unwanted effects: a) a slow drift of the background intensity due to the curvature and to the finite extension of the samples that lead to a lift-off variation and to edge effects respectively; b) a "salt & pepper" noise due to the high frequency noise components of the electrical signals acquired; c) a spatial spreading of the actual defect dimensions due to the spatial finite sensitivity of the Hall sensor, i.e. due to their impulse response. These effects are clearly evidenced in the top of Fig. 3 that illustrates a typical reconstructed image before the processing step. To tackle these issues, we have exploited different processing tools. In particular, we implemented a 2D high pass filter in the frequency domain to reduce the slow drift in the
background of the images while to enhance the resolution, as well as to reduce the noise, we have accomplished the deconvolution of the reconstructed images from the impulse response of the probes. As said, to reduce the effect of lift-off, sample curvature and edge effect, the data have been processed by means of a 2D high pass filter: an example of the resulting images after the filtering is reported at the bottom of Fig. 3. Once carried out the 2D filter, we have tackled the deconvolution issue. Precisely, we have deconvolved the filtered images from the impulse response of the probes. In the present work, due to the adopted measurement procedure (B, i.e. the magnetic field, was measured while the array was moving along the Y-axis, while different X values correspond to different probes of in the array), we have consider a 1D impulse response, equal for any of the Hall probes. This impulse response was attained by recording the signal produced by a single probe passing above a pointwise defect. Starting from this signal, we have performed the deconvolution task. As an innovative aspect of the present work, the deconvolution has been carried out by combining the standard linear Wiener filter [5] with the non-linear Independent Component Analysis, henceforth denoted as ICA [6]. In defining this procedure, we have supposed that ICA was able to separate the “true” images corresponding to defect patterns from the noise by exploiting its inherently non-linearity in the separation of components with mutual statistical independence. In particular, we assumed that the images corresponding to the defect patterns, viewed as 1D time-series of a variable $x$, are characterized by a super-gaussian statistic, while noisy components tend to be gaussian. The frequency behaviour of noisy components (mainly due to the impulsive response of probes) is, in fact, very similar to white gaussian noise. Moreover the effect of the convolution between defect patterns and impulse response of the probes, spreading the gamma of the images intensity values, lead to a mitigation of this super-gaussian feature. Usually, the standard deconvolution algorithms are based on the minimization of a quadratic
error functional that can only achieve the optimal trade-off between resolution gain and noise suppression. On the contrary, we exploited the ability of ICA to map the information from the $\mathbb{R}^{P \times Q}$ domain (where $P$ and $Q$ are the number of pixels along width and height of source images, respectively) into a co-domain where information is split into sourcing sub-information, by minimizing the mutual information [7] or maximizing the non-gaussianity of sources [8]. To gain insight how the deconvolution procedure work, let us first introduce some details on the ICA algorithm and then we report the overall developed protocol.

3.1. Independent Component Analysis algorithm

In the general framework of ICA, a number of different sources $s_j(\cdot)$ can be estimated starting from mixed sequences in the time- or space-domain $l_k(\cdot)$. Broadly, the algorithm is based on the determination of the mixing matrix $A$, and then the calculation of its pseudo-inverse $W$. Subsequently, the original sources $s$ can be recovered by multiplying the observed signals $l$ with the unmixing matrix $W$. There are many algorithms available in the literature which are capable to perform ICA. Due to our aims and its fast running, we exploited the FastICA [9] algorithm, which takes advantage of a fixed-point iteration scheme maximizing non-gaussianity as a measure of statistical independence. The algorithm finds the direction for the weight vector $w$ maximizing the non-gaussianity of the projection $w^T l$ for the data $l$. The function $g(\cdot)$ is the derivative of a nonquadratic nonlinearity. For example $g(u)$ could be the derivative of $G(u) = \frac{1}{a_1} \log \cosh a_1 u$, i.e. $g(u) = \tanh (a_1 u)$. The basic form of the FastICA algorithm is as follows: i) choose an initial weight vector $w$; ii) let $w^+ \leftarrow E \{ xg(w^T x) \} - E \{ g'(w^T x) \} w$; iii) let $w \leftarrow w^+ / \|w^+\|_2$; iv) if not converged, go back to 2. This one-unit algorithm estimates just one of the Independent Components, or one projection pursuit direction. To estimate several Independent Components, we need to run the one-unit FastICA algorithm using several units with weight vectors $w_1, \ldots, w_n$. To prevent different vectors from converging to the same maxima we must decorrelate the outputs $w_1^T l, \ldots, w_n^T l$ after every iteration. For instance, a simple way of achieving decorrelation is a deflation scheme based on a Gram-Schmidt-like decorrelation. More details can be found in [9].

3.2. Deconvolution procedure

In order to implement ICA combined with Wiener filter we have followed the following procedure:

1. we oversampled the image along the Y-axis direction, i.e. along the direction in which acts the convolution between impulse response and "true" image. The oversampling factor is equal to $N$ (typically ranging from 5 to 10)
2. we applied both the 2D high-pass filter and the Wiener filter to the oversampled image in the frequency domain
3. from the output of the Wiener filter we extract up to $N$ sub-images with the wanted final resolution along the Y-axis. These images represent the collection of signal arising from the same physical phenomenon at the input of the ICA analysis
4. at the output of ICA analysis, we attain $M \leq N$ independent signals: we retain only the one exhibiting the highest value of kurtosis. This signal represent the deconvolved image with pixel dimension equal to $2\text{mm} \times 0.5\text{mm}$. 

The reason of retaining the Independent Component with highest kurtosis is based on the main characteristics of useful signal. In fact, it is expected to be less gaussian than the impulsive response of probes, which have spectra similar to white gaussian noise.

4. Experimental Results

Figure 4. Result of ICA deconvolution, considering a plate with oxide scales.

Figure 5. Result of ICA deconvolution, considering a plate with oxide scales.
Some results attained by applying the procedure above described to experimental reconstructed images are reported. In order to fairly evaluate the deconvolved images with and without the ICA analysis, the following figures compare the output of the overall procedure with the image attained after the Wiener filter application. Since this image at this step has a higher resolution, we applied a moving average filter along the scan direction (with number of taps equal to the oversampling factor) and then we have downsampled the image in order to achieve the wanted resolution. All the images cover the same spatial dimensions of $256 \text{mm} \times 250 \text{mm}$ and have been acquired with the same oversampling factor ($N = 6$).

5. Conclusions

We reported the contextual application of the Independent Component Analysis and of the Wiener filter to the deconvolution of images attained by means of a Magnetic imaging apparatus. The proposed procedure allows to enhance the image resolution and to remove noise compared with the adoption of the solely Wiener filter. Moreover the ICA deconvolution stage suppresses the residual drift after the application of the high-pass filter. When implemented on defects characterized by a small area, the performance improvement is less evident. This can be due to the lower statistical relevance of the supergaussian component. In this case the procedure should be improved by slightly modifying the ICA analysis, for instance exploiting the Sparse Code Shrinkage [10].
Figure 7. Result of ICA deconvolution, considering a plate with a small pitting.

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References