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Establishment and validation of the Channelized Hotelling Model Observer for image assessment in industrial radiography

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ABSTRACT

A new method for industrial radiography is presented to assess image quality objectively. The assessment is performed by a modelled observer developed to interpret radiographic images in order to rate the detectability of structural defects. For the purpose of qualifying radiographic NDE procedures, computational tools simulate the image, but should additionally automatically assess the associated image quality instead of relying on human interpretation. The Channelized Hotelling Model Observer (CHO) approach, originally developed for medical imaging, is here developed for industrial NDE applications to measure objectively the defect's detectability. A validation study based on a comparison of the model's efficiency of observing circular and elongated flaws shows that the CHO outperforms other detectability models used by industry. Furthermore, the model's reliability was verified by comparing it to psychophysical data.

1. Introduction

X-ray imaging methods are used by industry, in a similar manner to the medical field, to investigate the inner structure of a specimen without causing harm by cutting. In the field of Non-Destructive Evaluation (NDE), conventional film based or digital X-ray inspection is applied for testing critical technical components across a number of industry sectors to identify structural defects like cracks. Hence, reliable optical image interpretation is essential.

Establishing the most appropriate radiographic setup for an inspection problem at hand can be very costly with regard to mockups and labour. Therefore, increasing the use of computational tools to simulate radiographic inspections is advisable. These tools help to find the test configuration which leads to the best possible image result. Moreover, reliable models allow the qualification of test procedures to be achieved more efficiently.

Radiography is based on the phenomenon of electromagnetic rays passing through the investigated object and attenuating as a function of the object's material properties. The remaining photonic energy having totally passed through the object induces a chemical reaction in the film exposed on the backside of the object. This reaction causes localised blackening of the film, producing an image linked to the actual physical conditions of the object.

The interpretation of the image is difficult because it contains not just a specific visual defect signal but also signals from the surrounding geometry, while scattering, noise etc. also influence the image. Therefore, the image needs interpretation by a human expert to identify damage signatures in the image. The human based evaluation step is crucial, because here it will be decided if there is a defect present or not. To improve the image quality, computer tools should be able to predict the defect's visibility for image assessment reasons, which can then be used to optimise the setup. This prediction completes the frame of a holistic simulation, besides modelling the test setup and simulating the image, and is also a prerequisite for Probability of Detection (POD) studies. In particular, the qualified expert's defect detection ability investigating an actual film based image should be anticipated by a computer model. So far, visibility criteria applied to perform that prediction task are available for industry [1–4], but these are only applicable with restrictions or under strong assumptions.

The objective of this work is to establish a new technique to measure the detectability more generally to predict better the defect's visibility. The presented method is fundamentally different to the methods currently used in NDE. This new method will improve the process of qualifying test procedures and allows the best radiographic test setup

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with regard to visibility to be found.

This article is divided into the following sections: First, a review of existing visibility criteria that are already used in NDE is given. Then a transfer of a Model Observer (MO) approach from the medical field to industrial NDE is provided, including its validation for industrial applications.

2. State of the art

The following paragraphs describe existing models to predict the human detectability of visual signals in industrial radiographic images.

2.1. Rose Model

The stochastic phenomenon of detecting photon quanta follows the Poisson distribution. The characteristic of the Poisson distribution is that its expected value and variance are equal. The accuracy of measuring the detected number of photons N depends on its standard deviation σ: the lower σ, the more likely is N close to the expected value. Or put another way, the lower σ is, the easier it is to distinguish smaller changes of N, referred to as ΔN, the smallest distinguishable change. This leads to the proportionality

$$\Delta N \propto \sigma. \tag{1}$$

Making use of the denoted distribution characteristic and the definition of the standard deviation

$$\sigma \equiv \sqrt{\mathrm{Var}(N)} = \sqrt{N} \tag{2}$$

it can be stated that

$$\Delta N \propto \sqrt{N} \tag{3}$$

or by introducing a proportionality factor k and rearranging

$$\frac{\Delta N}{\sqrt{N}} = k \tag{4}$$

which is called the Rose Model representing a signal-to-noise ratio. Visual experiments showed that a good approximated value of k should be around 5 to assure visibility [5–7].

2.2. EDF criterion

The EDF visibility criterion generates a visibility map of the whole image. This is done by measuring the average contrast in an elliptical area (area: 1.6 mm^2; eccentricity: 0.89) around every pixel of the image, while the ellipse is rotated stepwise. The maximum of the average contrast values in any position of the ellipse is taken as the visibility value associated to the pixel in the centre of the ellipse. The global visibility measure of the whole image is given by the maximum measure of all pixels. The visibility value is afterwards divided by the noise to get a contrast-to-noise ratio [1,2,8].

2.3. CEA criterion

The CEA criterion is based on the Rose Model but generalises it beyond circular features by also considering elongated shapes. It rests on the industrial standard [9] giving a reference that elongated shapes of a specific width should be distinguished by the same visibility as circular shapes of a specific diameter [3].

2.4. INSA criterion

The INSA criterion's major advantage compared to the classical Rose Model is that it takes the gradient of optical density that surrounds an image of a defect into account. That gradient can degrade the visibility wherefore it is introduced as a penalty factor to decrease the gross result of Rose's model [4].

2.5. CSF criterion

The CSF criterion is basing on the contrast sensitivity of the human eye [2]. The Contrast Sensitivity Function (CSF) describes how the human eye is sensible to a visual signal in dependence of its contrast and spatial frequency [10,11]. The image is 2D Fourier transformed and an averaged 1D spatial frequency spectrum is calculated. That generalised frequency spectrum is afterwards weighted by the CSF, then summed, normalised and divided by the noise level, in order to get a visibility measure [2].

3. Model Observers

Medical radiographic imaging has pressure to reduce radiation exposure to the patient, but also ensure that lesions are still detectable. Therefore models have been developed in the medical field to quantify the image quality in terms of signal detectability. This lends the previous work conveniently to our subject of NDE, where we have similar objectives.

The task of image quality definition has to be performed objectively. Image quality is defined as how well desired information can be extracted from an image [12], generally by an observer. Model Observers (MO) are mathematical constructs to imitate the human process of visual recognition. They are developed in comparison with psychophysical studies in order to imitate human perception. Image quality measurements can be done by quantifying the detection performance of a mathematical observer model treating the image under investigation. As a result, the image quality is measured objectively and the human performance can be derived from the MO's performance [12].

The formation of an exemplary MO will be described in the following paragraphs.

3.1. Theory and definitions

The process of imaging an object can be described by

$$\mathscr{H}(\boldsymbol{f}) + \boldsymbol{n} = \boldsymbol{g} \tag{5}$$

where $\boldsymbol{f}$ denotes the object being imaged, $\mathscr{H}$ the imaging function representing the imaging system, $\boldsymbol{n}$ the noise generated during the measurement and $\boldsymbol{g}$ the image [13]. For better convenience, the image, normally stored as a matrix of pixel values, shall be transformed into a vector by lexicographical indexing: the rows of the matrix are transposed and successively concatenated to form a vector containing all the information of the original image representation.

All MOs compute a scalar variable, called test statistic λ. That test statistic is compared to a decision threshold λ_t to hypothesise whether the image belongs to a “signal-present” or “signal-absent” class [12,14,15]. Fig. 1 describes schematically the image production and decision process.

The key question is how the observer computes the test statistic. The work presented here is restricted to linear observers, which compute the

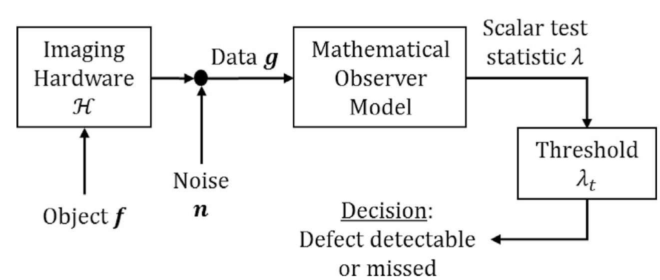

Fig. 1. Flow chart illustrating the deciding process of an observer [19].