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**Automating defect visibility assessment in industrial
radiography and realistic film noise modelling based
on experimental investigations**

by

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Abstract

Radiography is one of the main methods within the industrial field of Non-Destructive Evaluation (NDE). It is a projection imaging technique relating the subsurface information of the structure under investigation to a greyscale valued image. In order to ensure operational reliability, inspection procedures need to be qualified before the actual evaluation takes place in practice. Alongside experiments, this qualification process often involves computational tools to model various possible test setups incorporating artificial defects, producing a simulated image. Then the simulated image is assessed, which is traditionally performed subjectively by an operator deciding on the visibility of an artificial defect. If the detectability of that defect is increased, then the underlying parameters of the considered test procedure are preferred.

Two crucial aspects of the stated qualification process are addressed within this thesis. Firstly, the presented work advances the simulated qualification approach to a more holistic one by not only modelling the test setup and simulating the resulting image but also by assessing the simulated image automatically. A Model Observer approach is chosen for automating the interpretation of the simulated images. This approach is based on the so-called Channelized Hotelling Observer (CHO), which was originally established in the medical field but is now transferred to NDE. Validation of the new assessment approach is done by comparing experimental psychophysical data of human image assessment to the performance of the CHO in assessing simulated radiographic images. The new method outperforms other state-of-the-art visibility models currently used in industry.

Secondly, the correct simulation of the artificial radiograph is crucial for an accurate computational qualification of the test procedures. An important part of the radiograph is the underlying noise, which has a great influence on the image quality. Industrial radiography still mainly relies on films as detectors, since these are reliable and well established over decades. These films show a typical film noise granularity, which usually degrades the defect visibility. Therefore, it is crucial to incorporate realistic film noise in the simulation by a sophisticated film noise model. Currently, the industry considers only white Gaussian noise, which is unrealistic. A new noise model based on experimental investigations of real noise on film samples is presented. It is shown that very realistic artificial noise can be generated by extracting and utilising the spectral characteristics of the real noise. The method generates new and unique noise samples by randomising the phase spectrum but keeping the original spatial frequency spectrum. Furthermore, the method allows the generation of noise with local, space depending spatial frequency spectra while ensuring pixel correlation throughout the image. Various validation studies show that the noise generated by this new method is visually and statistically indistinguishable from the original noise.

Additionally, a new optical setup for digitising radiographic films on the microscale is presented. This setup is based on a digital camera and image processing procedure enabling the extraction of the film noise spectra that can then be used to generate film noise realistically. Homogenously exposed and developed films are investigated by the new setup in order to generate a database of spectral properties necessary for the generation of accurate film noise. Furthermore, the new setup can efficiently classify the quality of film systems without relying on time-consuming microdensitometer measurements, which is an important secondary benefit of this new setup.



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Declaration of Originality

I herewith certify that all material in this dissertation which is not my own work has been appropriately acknowledged and references are provided wherever the work of others has been used.

Sebastian Eckel, M.Sc.

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Nomenclature

$\emptyset$	diameter
$\bar{a}$	mean projection area
A	film area
A_d	defect area in INSA criterion
A_{eq}	equivalent area
A_{max}	maximal area in CEA criterion
A_p	pixel area
$\mathbf{b}$	image background
$B(x, y)$	image pixel value at position (x, y)
B_S	scene brightness
C	contrast
c	cumulative histogram
C^{GLCM}	GLCM contrast feature
C_t	threshold contrast
$d(\mathbf{x})$	signal at position $\mathbf{x}$
d_{GL}	maximal grey level difference
F	target CDF
$\mathbf{f}$	object being imaged
$\mathcal{F}_{2D}\{ \}$	2D Fourier transform
ff	flat field image
G	CDF of the Gaussian distribution

$\mathcal{F}$	Fourier transformed image
g	Gaussian PDF
$\mathbf{g}$	image
$\mathbf{g}_1$	image containing the flaw signal
$\mathbf{g}_2$	image without the flaw signal
GL_{max}	maximal greyscale level
$GLCM$	Grey Level Co-occurrence Matrix
h	filter
H	filter frequency response
$\mathcal{H}$	imaging function
h_A	side length of the area under investigation
$\mathbf{i}$	unit imaginary number
$\tilde{I}$	noisy image
i_{CEA}	CEA criterion shape factor
I_{CEA}	CEA criterion visibility indicator
I_{input}	input image without noise
I_{INSA}	INSA criterion visibility indicator
I_{OD}	image in OD values
i_P	pixel intensity
I_{raw}	raw image
$\mathbf{K}$	covariance matrix
$\mathbf{K}_{CHO}$	covariance matrix of the channel response
k_R	Rose model proportionality factor
L	number of used filters

l_{eye}	minimal resolution of the eye
L_f	length of a flaw
l_{pix}	pixel size (resolution)
M	total pixel number
m, n	matrix dimensions
N	image of the pure noise fluctuations
$\mathbf{n}$	image noise
n_A	number of exposed particles in the area A
N_A	number of photons radiating an area A
N_C	number of frequency selective channels
N_{norm}	normalised noise image
N_{OD}	noise image in OD values
N_q	number of quanta (photons)
N_s	number of samples in the population
n_{si}	number of sub-images
NPS	Noise Power Spectrum
OD	(visual diffuse) Optical Density
OD_{bg}	Optical Density of the background
OD_{flaw}	Optical Density of the flaw
p, q, k, j	iteration counts
p_l	path length
p_x, p_y	dimension in number of pixel in the x (respectively y) direction
Q	filter-width ratio
Q_C	Callier factor

R	radiation intensity
R_0	initial radiation
r, θ	polar coordinates in radial and circumferential directions
r_S	shape ratio
s	flaw signal
T	bank of channel filters
T	filter matrix
t	transmittance
u	channelized image
U	Fourier transform of u
u, v	spatial frequencies in both Cartesian directions
U_f	film system unsharpness
u_{wg}	white Gaussian noise
v	filtered white Gaussian noise
V	greyscale transformation function
w	noise image (fluctuations)
w	weighting vector
W	width
x	pixel position
X, Y	dimensions of the noise image in both spatial directions
Z	2D autocorrelation of normalised noise image
α	angle
γ	autocorrelation function
δ	weighting factor

$\Delta x, \Delta y$	offset between two investigated pixels
λ	test statistic
λ_{CHO}	test statistic of the CHO
λ_t	decision threshold
λ_{Hot}	Hotelling Observer's test statistic
μ	linear attenuation coefficient
ν, ξ	coordinates in the Fourier domain
ρ	spatial frequency
ρ_c	cut-off frequency
σ	standard deviation
σ_{film}	noise standard deviation of real film
σ_{noise}	standard deviation of noise
Φ_e^i	radiant flux received
Φ_e^t	radiant flux transmitted

Abbreviations

AgBr	Silver Bromide
BAM	Bundesanstalt für Materialforschung und –prüfung – German Federal Institute for Materials Research and Testing
CDF	Cumulative Distribution Function
CEA	Commissariat à l'énergie atomique et aux énergies alternatives – French Alternative Energies and Atomic Energy Commission
CHO	Channelized Hotelling Observer
CSF	Contrast Sensitivity Function
DDA	Digital Detector Array
DFT	Discrete Fourier Transform
EDF	Électricité de France SA
EPSRC	UK Engineering and Physical Sciences Research Council
ESF	Edge Spread Function
FFT	Fast Fourier Transform
GLCM	Grey Level Co-occurrence Matrix
GV	Greyscale Value
ICASE	Industrial Cooperative Award in Science & Technology
IFFT	Inverse Fast Fourier Transform
INSA	Institut National des Sciences Appliquées – French National Institute of Applied Sciences
IQI	Image Quality Indicator
keV	Kiloelectronvolt
LSF	Line Spread Function

MAFC	Multiple-Alternative Forced Choice
MeV	Megaelectronvolt
MO	Model Observer
MTF	Modulation Transfer Function
NDE	Non-Destructive Evaluation
NDT	Non-Destructive Testing
NMS	Noise Magnitude Spectrum
NPS	Noise Power Spectrum
OD	Optical Density
OTF	Optical Transfer Function
PDF	Probability Density Function
PET	Polyethylene Terephthalate
PMF	Prewhitening Matched Filter
POD	Probability Of Detection
RCNDE	UK Research Centre for Non-Destructive Evaluation
RDM	Random Dot Model
ROI	Region Of Interest
SNR	Signal to Noise Ratio

Introduction

1.1 Industrial context

Industrial radiographic testing, also referred to as industrial radiology, is a well-established method within the industrial field of Non-Destructive Evaluation (NDE), also known as Non-Destructive Testing (NDT). NDE is an area in science and technology industry that combines all examination techniques used to investigate the structural integrity and quality of a mechanical component without causing any permanent change to the structure. NDE techniques are applied in order to detect and characterise internal, surface or near-surface structural defects such as cracks, inclusions or internal voids to prevent and to manage the risk of failure of components that are in-service and to improve the quality of components during the manufacturing process. By using NDE results in comparison to or within structural integrity calculations, it is possible to make probabilistic predictions of a components' lifetime. NDE enables one to make sure that a component is left in service only if the flaws that are present and detected can be rated as acceptable under safety and economic aspects, i.e. by demonstrating that the defect size is not critical. In that sense, NDE brings also an important economic benefit by proving that an impeccable component is free of critical defects and does not need replacement even though it might have already been running for a particularly long period of time. As there is always a trade-off between the risk of failure and the cost of replacement, one benefit of NDE is that it has the potential to allow well-founded decisions to be made

about whether the component needs immediate replacement or when the next inspection should be due to monitor the defect growth and update the risk assessment. It should be highlighted that the risk is twofold: it includes the risk how confidently decisions in consideration of the severity of the detected defects can be made as well as the risk of whether the present defects were characterised correctly or detected at all by the applied NDE method. Any NDE method can only detect flaws of a case-specific minimum dimension and this knowledge is also taken into consideration while reaching decisions. Regular inspections offer the possibility to monitor the defect and to improve predictions on the component's remaining lifetime.

Accidents causing harm to people and the environment or economic loss occur when a structural component fails unexpectedly while handling any mechanical system such as an aeroplane, running a chemical plant or simply when using a ladder that might break when climbing up. NDE is substantially responsible that these failures and related accidents do not occur. Being of such great importance for our daily lives, most people are not aware of its significance or even presence at all. For these people, the importance of NDE might only become obvious in the case of failure when the emergency happens but hidden when NDE is operating correctly and modestly in the background. Today, NDE is applied to any safety-relevant technical component or structure such as vessels, pipes or welded joints [1].

A broad overview of the most important NDE techniques and a comparison between them is conducted in the following paragraphs. Furthermore, the motivation for the presented research as well as the organisation of the project and the thesis structure will be presented.

1.2 Main NDE techniques

Radiographic testing is a projection imaging technique based on the phenomenon of electromagnetic rays passing through the investigated object and attenuating primarily as a function of the object's density along the travel path. The industrial component under investigation is radiographed by radiation such as X- or γ -rays. The radiation is directed on the front of the object, passes through the object and will be partially absorbed and scattered. A radiation detector is placed on the back side of the object to measure the remaining radiation passed through the object. Traditionally, radiation sensitive film is used as a detector, but more and more digital detectors such as imaging plates or Digital Detector Arrays (DDA, also known as Flat Panel Detectors) are used. However, films are still widely used particularly in areas such as the nuclear industry which rely on well-established and reliable detectors. Films have been developed over almost a century whereas digital detectors have emerged much more recently. Film-based testing can also be quicker and cheaper with reduced calibration effort compared to digital alternatives. It is expected that film will still play a major role in NDT at least in the nuclear industry for the next 10 years. The spatial distribution on the detector of local radiation absorption is a two-dimensional representation of the absorption and scattering characteristics within the three-dimensional object. The generated dataset is effectively a shadow image assembling greyscale values that represent the object's subsurface information in an integrated form. The integration is performed over the straight ray path through the object and disturbed by scattered radiation. The image is linked to the actual physical conditions of the object. The interpretation of the image is challenging because it contains not just a specific defect but also the surrounding geometry, while scattering, noise etc. also influences the image. The detector is a main source of

noise affecting the image. This can be either grain noise, such as for film-based radiography, or noise caused by digital detectors. Besides electronic noise, digital detectors have also a coherent fixed noise pattern that is caused by the structural layout of the digital detector. Therefore, the image needs interpretation by a skilled human inspector to identify damage signatures. This interpretation is opposed to other NDE techniques producing an electrical signal that can be evaluated in a more procedural manner. The schematic in Figure 1.1 gives an overview of the radiographic process with the intensity profile in a one-dimensional representation.

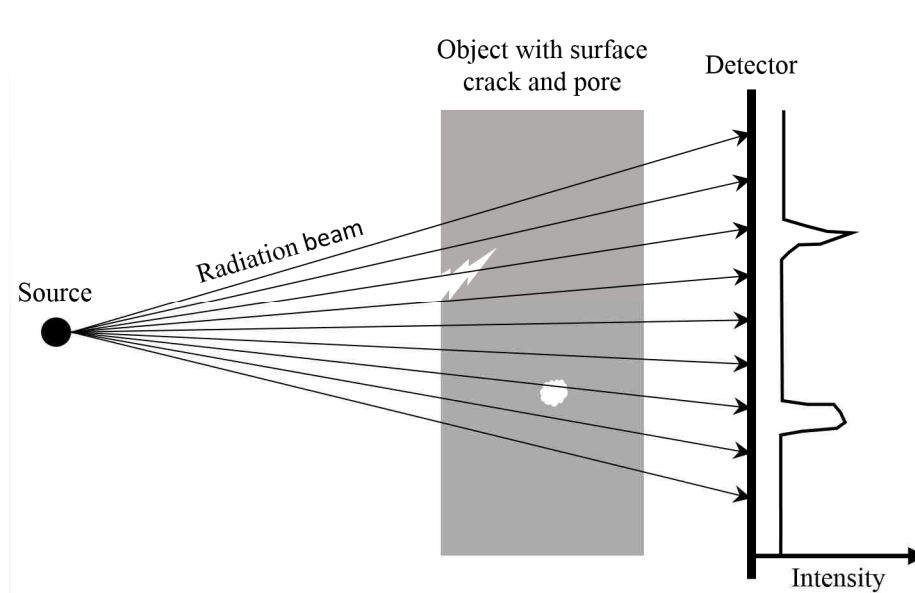


Figure 1.1 *Schematic of the radiographic process including the intensity profile formation in one dimension*

Besides being applied in industrial NDT, imaging radiology is a major examination method of biological tissue in medical diagnostics. However, high energy electromagnetic radiation such as X- and γ -rays is ionising and hence damaging biological tissue. Herein lies a major difference in industrial radiology to its medical use. In medicine, radiation doses are set to be as low as possible in order to prevent or reduce harming the human object. In the industrial

environment, ionising radiation has usually no practical impact on the object and can and must be much higher than in medicine in order to achieve a good image quality. The main health safety challenge in industry is to prevent humans operating in the surrounding area of the test from being affected by radiation while high doses are necessary to radiograph dense and thick mechanical components. Because of the hazardous nature of ionising radiation, many legislations regulate the use of radiographic inspections in practice. Before performing radiographic testing, rigorous planning for the job and a risk assessment stage including the elaboration of emergency procedures in case of a radiation accident should precede the actual exposure in order to prevent any harm to workers and uninvolved people. For example, the precautions start with the handling of radiographic sources, especially gamma sources, include preparations for closing and shielding of the examination area and go over to measures for directing the ray beam by using appropriate collimators. These precautions explain why radiographic inspections can only be conducted securely and reasonably after a sufficiently long preparation period increasing the overall inspection costs significantly. Because of the inherent risks of ionising radiation, there is a tendency to search for harmless replacement techniques such as ultrasound. [2], [3]

Alongside industrial radiology, ultrasonic testing is another technique able to detect defects throughout the object volume. Ultrasonic testing combines methods investigating the inner structure of an object by mechanical (acoustic) waves. For example, an ultrasonic probe is placed in contact with the object emitting high-frequency sound waves into the medium. Usually, a couplant is used between the probe and the object to improve the coupling. Either the transmission or the reflection (echo) of the wave is then measured by the same probe (pulse-echo technique) or by a second probe (pitch-catch technique).

Scanning across the surface enables a two-dimensional image representation of the internal structure of the object to be obtained.

Comparing ultrasonic testing with radiology, it can be stated that radiography is a good tool for flaw characterisation and sizing [4]. However, specifically for crack detection, radiography is less sensitive in detecting cracks with small angles and with a complex shape or if the plane of the defect is perpendicular to the ray beam as their small volume does not affect much the passing of the rays. These can be better detected by ultrasonic testing specifically sensitive to crack surfaces [4]. Roughly speaking, radiography is more sensitive to pores and ultrasonic testing to tight cracks. Concerning the material, radiography is more sensitive to flaws in thinner components because lower necessary radiation energy leads to increased detectability. On the other hand, ultrasonic testing is less affected by the specimen thickness as long as the material does not significantly scatter ultrasonic waves. Materials with a coarse microstructure, where the constituents' dimensions are of the same order as the ultrasonic wavelength, are highly scattering to ultrasonic waves and provide a significant challenge to be inspected by ultrasonic methods. For example, developments in high temperature, creep resistant metals improving the efficiency of thermal power plants are coarse-grained and polycrystalline. The inspection of these materials is difficult by ultrasonic techniques due to strong coherent noise caused by scattering affecting the measured signal [5]. Radiographic testing is therefore traditionally favoured for testing these highly scattering materials [4] and is therefore vital for testing e.g. in nuclear power plants. Additionally, radiography is preferably applied when hidden areas of the object are investigated and preparation of the object such as removal of insulation needs to be minimised. However, the safety while performing radiography is a major challenge and the harmful ionising radiation is

not visible by the naked eye, whereas ultrasonic testing is completely harmless to the human operator.

Other NDE techniques investigate mainly the surface or near-surface properties of the object rather than the whole volume, such as:

- *Magnetic particle inspection is a method primarily used to detect surface or near-surface cracks in ferromagnetic materials. The inspection area is sprayed uniformly with fine iron particles. Then, the area is magnetised and cracks crossing the magnetic flux line distort the magnetic field causing magnetic flux leakage. The leakage can be made visible by the built-up of the fine iron particles accumulating around the crack.*
- *Eddy-current testing is an inspection method for electroconductive materials. An electromagnetic coil is moved over the surface of the object inducing a magnetic field resulting in eddy currents on the surface of the object. The generated eddy currents are measured and surface or near-surface defects can be identified because they change the eddy currents locally.*
- *Liquid penetrant inspection is a method for surface-breaking defects only but applicable to any material that is not porous. A coloured liquid is applied to the surface penetrating into the defects due to their capillarity. Afterwards, the penetrant is washed off from the surface only and a developer usually of white colour is applied absorbing locally the remaining penetrant in the defects. Clear indications become visible where the developer becomes coloured due to the local absorbance of the remaining penetrant.*

- *Visual inspection* is used to identify optically discontinuities on the surface of the object of any material with or without the use of optical aids.

Method	Defect detection within the volume	Near-surface defect detection	Surface defect detection
Radiography	✓	✓	✓
Ultrasonic testing	✓	✓	
Magnetic particle inspection		✓	✓
Eddy-current testing		✓	✓
Liquid penetrant inspection			✓
Visual inspection			✓

Table 1.1 Various NDE methods and their ability to detect surface breaking, near-surface or defects within the volume

1.3 Motivation and problem statement

Nowadays, analogue film-based radiographic inspection techniques are still a very important instrument for non-destructively testing critical parts e.g. in the

nuclear or the oil and gas industry, despite the increasing use of digital detectors. These inspections can be very costly with regard to material and labour and possibly hazardous for the operator due to the ionising radiation. Therefore, the French energy company “Électricité de France SA” (EDF) – the industrial sponsor for this project – tries to utilise computational tools as much as possible for each radiographic inspection to find the test configuration which leads to the best possible results when trying to detect defects in industrial components. Furthermore, simulation approaches allow NDE inspection procedures to be qualified by studying the impact of various test setup parameters (such as angles, distances, energies etc.) allowing the robustness of a proposed examination procedure to be checked. In this work, the radiographic simulations were performed by EDF’s in-house simulation package MODERATO [6]. Radiographic projections are simulated by this code using the analytical Beer-Lambert approach of straight rays. Additionally, scattering can be modelled by random walks of photons based on a Monte Carlo approach.

This thesis addresses two current problems of the state-of-the-art in radiographic simulation for testing assessments. In industry, modelling of the test setup including the object with artificial defects and simulating the resulting radiograph is well established. However, in order to improve the setup, the resulting simulated radiographic image needs to be assessed by a human expert regarding the defect visibility. Better defect visibility means a better and more favourable setup for the real investigation in practice. The first problem addressed in this thesis is to automate the assessment process of the simulated radiograph. The aim is to come to a truly holistic simulation of the radiographic investigation. Not only should the test setup be modelled and the resulting image simulated but also the human performance in observing a defect in the image should be predicted. That performance can then be used as a measure of the image quality.

It should be highlighted that it is not the aim of this work to detect defects automatically. The aim is to simulate the human detectability of an artificial defect that is unknown by the hypothetical human observer but known by the computer model.

The second problem concerns the simulation of film-based radiographs in particular. When an image is captured on a film, the image is disturbed by a specific film noise. That film noise is mostly caused by clustering of image-forming particles within the film. Film noise is an obstacle in detecting defects reliably and therefore the noise has a major influence on the image quality. It was stated earlier that the image quality in terms of defect detectability is an important measure for image assessments to improve test setups. Therefore, that noise needs to be considered in the simulation realistically in order to make reliable predictions on the quality of the setup. The second main achievement of this thesis is the presentation of a new model to simulate film noise realistically.

The film model introduced relies on experimental data gathered from real film samples, which is one of the main advantages of the presented model. Experimental investigations of real films are therefore also within the scope of this thesis. Films have been exposed and developed and subsequently digitised in fine detail by a new optical setup to digitise film samples introduced in this thesis. The setup is mainly based on a digital camera and image processing procedure digitising films correctly on a microscale.

1.4 Project organisation

This PhD project was run at Imperial College London in collaboration with EDF in Pairs, France. Supervision was provided by Dr Peter Huthwaite (principal

supervisor), Prof. Mike Lowe (secondary supervisor) and Dr Andreas Schumm (industrial supervisor). The author was granted with an Industrial Cooperative Award in Science & Technology (ICASE, number 15220134) by the UK Engineering and Physical Sciences Research Council (EPSRC). Furthermore, this project was aligned with the UK Research Centre for Non-Destructive Evaluation (RCNDE). The work was carried out in the Non-Destructive Evaluation Group in the Department of Mechanical Engineering at Imperial College London. EDF provided the industrial context, relevant radiographic data and guidance for the project. Throughout the project, a fruitful collaboration with the Radiological Methods Division at the Federal Institute for Materials Research and Testing (BAM) in Berlin, Germany, was maintained. BAM is a scientific and technical federal institute with the mission to improve high standards for safety in technology and chemistry. BAM is under the charge of the German Federal Ministry for Economic Affairs and Energy. Its Radiological Methods Division is an internationally distinguished authority on research and standardisation related to industrial radiology. The collaboration provided an experimental element to the theoretical work of this project and enabled the author to spend two research stays (of a length of two and four weeks) at BAM in Berlin.

1.5 Thesis structure

The thesis begins with Chapter 2 giving some important background on radiographic testing. Furthermore, the basics and application of the Fourier transform to images of two dimensions are presented. This is the most important tool for the image processing tasks presented in this thesis.

Chapter 3 introduces a new detectability model based on the so-called Hotelling Observer originally developed in the medical field. The presented method allows

assessing the quality of simulated radiographs objectively. This work has been published as a journal paper in NDT&E International [7]. In addition, it was presented at the conferences QNDE 2017 and ECNDT 2018.

The need for a more realistic and sophisticated film noise model was emerging when the detectability model was developed. Therefore, Chapter 4 describes a new model to simulate radiographic film noise realistically. The presented method is based on data of real noise obtained by experimental investigations. The highlight of the model is its ability to generate noise with local, space-varying spectral characteristics. Besides the model's high performance in simulating realistic film noise for industrial radiography, it is much more general and can be utilised in any other field where the generation of non-stationary 2D noise with local, space-varying statistical properties is necessary. This work has been accepted as a journal paper by IEEE Transactions on Image Processing [8]. In addition, the progress of the work was incrementally presented at the conferences QNDE 2018, ECNDT 2018, DIR 2019 and QNDE 2019.

In order to gain and deliver the experimental input data for the presented noise model, Chapter 5 introduces a new optical setup and image processing procedure for detailed film sample digitisation. The method delivers the experimental data necessary for simulating film noise correctly. Furthermore, specific statistical characteristics of film noise are theoretically derived and subsequently verified by the data obtained by the presented method. Additionally, the new setup can be used for film system classification and therefore replaces time-consuming microdensitometer measurements that are traditionally required. This work was performed in intense collaboration with BAM and submitted as a journal paper to NDT&E International [9]. In addition, the work was presented at the conferences DIR 2019 and QNDE 2019.

Finally, Chapter 6 gives a conclusion of this work. The industrial impact is highlighted including implementation projects arising from the presented work. These implementations are currently being undertaken in industry and at research institutions. In addition, possible future work is discussed.

Background

In this chapter, background knowledge on the physical principles of radiography will be given followed by a presentation of the equipment for radiographic testing. The second part of this chapter is dedicated to introducing the Fourier transform in two dimensions as being a crucial tool for the image processing problems dealt with in the main chapters of this thesis.

2.1 Radiographic testing

2.1.1 Principles

This section introduces the fundamental principles of radiographic testing. The explanations in this section are based on the traditional volume “Industrial Radiology – Theory and practice” by Ron Halmshaw [4].

As already introduced in Chapter 1, radiography is an imaging method based on high energy electromagnetic rays emitted by a source and directed on and penetrating through the object from the front to the back side in straight paths, partially absorbed by the object matter and distorted to some extent by scattering. On their way through the object, the rays are attenuated and scattered depending on the object thickness and local material condition. Thinner parts of the object are better penetrated by the radiation. Local structural anomalies such as pores and cracks lead to a local variation in the thickness the rays must travel through and inclusions lead to a local material variation. The

remaining electromagnetic energy which has reached the back side of the object is then interpreted as the signal to be recorded by a detector. A spatial, two-dimensional image of the thickness and material variations along the ray path is produced on the detector. Any point in that image represents the objects' attenuating behaviour along the ray path in an integrated form. Rays penetrating the object on less absorbing or scattering paths cause a higher measurable radiation and so a stronger signal at the detector. The attenuation is usually energy-dependent. It is assumed that all the photons possess the same energy, then the attenuation of the radiation intensity R is described by [10]

$$-\int_{R_0}^R \frac{dR}{R} = \mu \int_0^{p_l} dp_l \quad (2.1)$$

with R_0 as the initial radiation intensity exposing the object from the front, the linear attenuation coefficient of the object material μ and the path length p_l on which the rays are travelling through the object. If the object material is attenuating homogeneously over the ray path, then the radiation intensity R that is reaching the detector after having passed through the object can be calculated by the Beer-Lambert law taking into account the initial radiation intensity R_0 ,

$$R = R_0 e^{-\mu p_l}. \quad (2.2)$$

An intuitive description of this is that the radiograph is formed in a very analogous way to the formation of a shadow image of a semi-transparent object by exposure with visible light. Flaws can be distinguished from undamaged material by interpretation of the generated radiographic image.

An important question is what radiation energy should be used to expose the object when producing a radiograph. The energy to be chosen for the radiographic investigation depends on the thickness and material of the object. A very dense and thick object needs higher energetic radiation to be able to pass

through the object in order to be detectable on the back side. However, higher energy is less affected by small thickness changes in the object and therefore has reduced sensitivity compared to lower energy. The detectability of flaws in the object is then reduced. On the other hand, lower energy produces images with higher contrast but also increases the necessary exposure time to form an image on the detector. The exposure time is defined as the amount of time that the object is penetrated from the front by radiation while a detector is recording the remaining radiation on the back side of the object. Hence, choosing the right radiation is always a compromise between sensitivity, penetrating power and exposure time.

When producing a radiograph, in order to achieve good image quality, there are compromises involving the available equipment and exposure time. Image quality is defined as the visibility of the defect on the radiograph and therefore as the detectability of the defect. An image with a better visibility of the defect is of better quality. Image quality is affected by three main parameters: contrast, unsharpness and noise. First, contrast describes the signal difference on the detector between the signal of an object and the background signal. A higher contrast increases the visibility of defects with smaller thickness or density variation compared to the surroundings. Second, the unsharpness describes the inability of the radiographic system to image a perfectly sharp edge on the object. The unsharpness introduces always some blurring in the image. Third, a radiograph always has a noisy, granular look. This granularity of the image is caused by spatial fluctuations of the radiation as well as inhomogeneities and imperfections within the detector reducing the detectability of small flaws if they are similarly sized to the graining. A main contribution of this thesis is the investigation of the radiographic granularity in Chapter 4 and Chapter 5. An important measure of image quality is the ratio between contrast and noise.

2.1.2 Radiographic equipment

The main equipment for performing radiographic investigations in industry is presented in the following paragraphs. This includes the radiation sources and the detectors.

Sources

The only physical difference between the electromagnetic radiation used in radiology and other electromagnetic radiations such as visible, ultra-violet or infrared light is their frequency or wavelength. Radiation with higher frequency and therefore quantum energy is able to penetrate objects that are completely opaque to low energy electromagnetic radiation such as visible light. For radiology purposes, high-frequency X- or γ -rays in the range of 10 keV up to 10 MeV are used. These two radiations are physically alike but they differ in their origin.

X-ray tubes

X-rays were discovered by the German mechanical engineer and physicist Wilhelm Conrad Röntgen in 1895 [11] and can be produced by an X-ray tube. In a vacuum tube, electrons are emitted from a cathode, accelerated by a high electric potential difference and colliding with an inclined target anode, e.g. made of tungsten, collecting the electrons. As the electrons are abruptly decelerated, their kinetic energy is transformed mainly into thermal energy and to a smaller extent into electromagnetic radiation, which leaves the tube through a vacuum-preserving window outlet. When the electrons collide with the target there is significant thermal energy emitted, making it crucial to cool the target. The process of X-ray generation within a tube is illustrated by the schematic in Figure 2.1. The high tube voltage between the cathode and anode controls the electrons' kinetic energy and therefore the energy of the emitted X-rays and

ranges usually between 10 kV and 10 MV for industrial radiographic applications [4]. In radiology, the tube voltage is used to indirectly describe the energy of the generated X-rays. However, the emitted X-ray photons do not all have the same specific single discrete energy value but the X-radiation instead possesses a continuous energy spectrum. Nevertheless, specific and discrete spikes overlay the continuous background, see Figure 2.2. As already mentioned, the abrupt deceleration of the electrons resulting in a momentum change produces electromagnetic X-rays. That radiation is called Bremsstrahlung (the German word for braking radiation) and is represented as the continuous background within the spectrum. The maximum energy value of the Bremsstrahlung is defined by the tube voltage, whereas a tube voltage of 300 kV would result in X-rays of a maximum energy of 300 keV. Besides the Bremsstrahlung, so-called characteristic radiation is also produced and superimposed on the continuous Bremsstrahlung spectrum, visible as spikes in the overall spectrum. When an electron with sufficient kinetic energy strikes a target atom and is able to eject an electron of an inner atomic shell within the target material, an electron from an outer shell will fill the generated gap. This transition of the electron from the outer to the inner shell – at discrete levels – involves a change in the energy level of the bound electron from high to low, and the difference in energy is emitted as a photon at a specific energy level. These photons make up the characteristic radiation and are specific to the target material, reflecting the different energy levels in the electron shells.

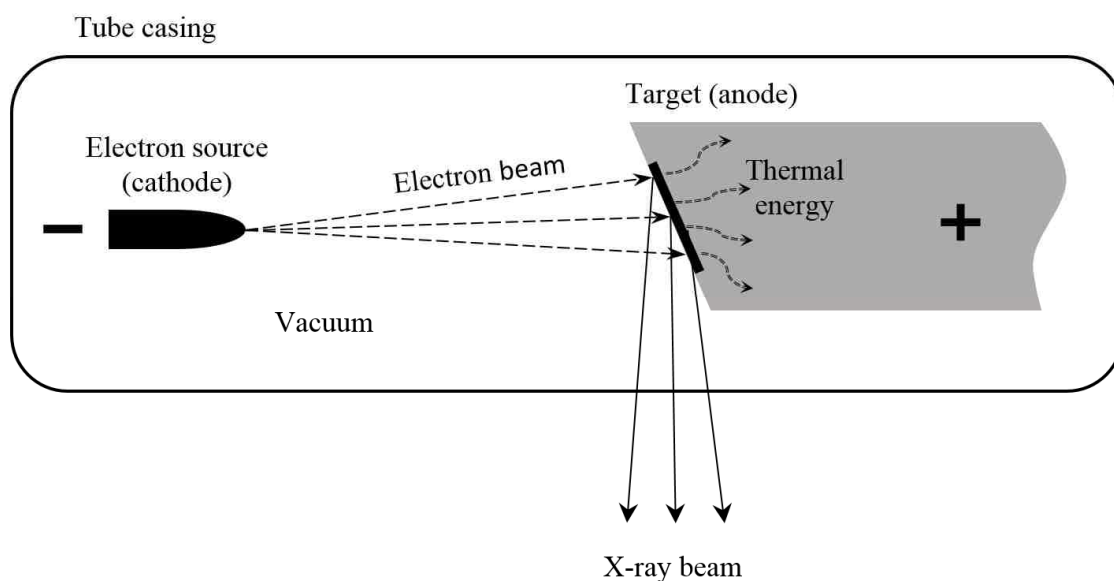


Figure 2.1 *Schematic of X-ray generation by vacuumed X-ray tube*

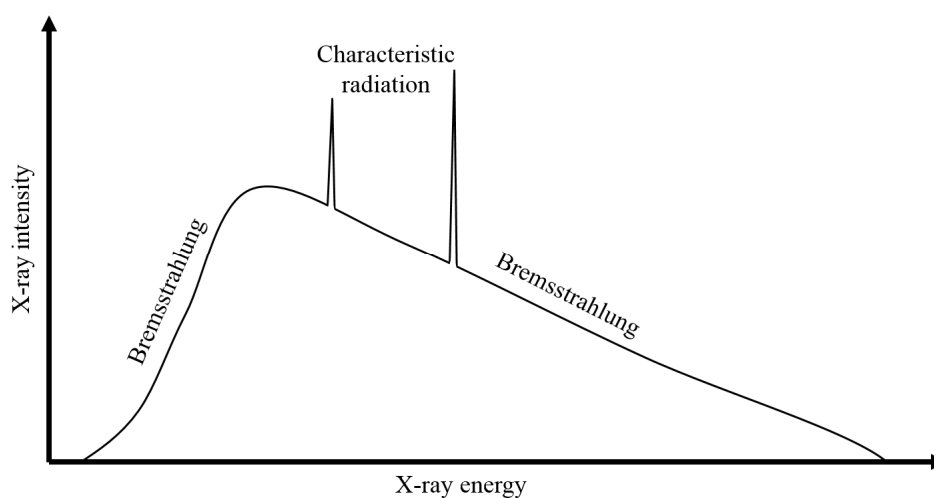


Figure 2.2 *Schematic of an X-ray spectrum consisting of a continuous part caused by Bremsstrahlung and a superimposed line spectrum due to characteristic radiation*

The spectrum of an X-ray tube can be modulated by placing a filter at the radiation outlet of the tube. These filters are metallic disks usually made of

copper, tin or steel with an appropriate thickness in relation to the voltage of the tube (around 0.1 mm up to 10 mm). The metallic disk works as a high-pass filter for the radiation removing low-frequency parts of the X-ray spectrum. As a result, the beam consists of a higher proportion of high energetic rays, often described as the beam being “hardened”. Low energy radiation is removed from the spectrum because it almost does not penetrate the object or penetrates only very thin parts, however, it leads to a very strong signal on the detector in areas where the beam reaches the detector freely without interaction with the object. This causes artefacts in the images with a local change of the X-ray spectra at the detector. Therefore, a prefiltering at the tube is advisable in order to homogenise the spectrum of the X-rays throughout the detector. Hence, the main practical use of beam prefiltering is to extend the imageable wall thickness range of the detector.

γ -ray sources

In contrast to X-rays, γ -rays are emitted from a radioactive isotope by nuclear decay. Radioactive decay is caused by an unstable atomic nucleus transforming into another nucleus emitting energy whilst changing its quantum state. The energy is emitted by α , β , or γ -radiation, depending on the specific isotope. The three types of radiation differ in their constitutive particles, such as helium nuclei for α -rays, electrons or positrons for β -rays and photons for γ -rays. The γ -rays are physically similar to X-rays but the energy spectrum of γ -rays is a discrete line spectrum rather than continuous as is the case for X-rays. This is true as long as there is no Bremsstrahlung involved which may be caused by the emission and deceleration of β -radiation within the isotope itself. γ -rays are usually characterised by a higher frequency and therefore higher energy than X-rays. Common radioactive isotopes for industrial radiology are Iridium-192 or Cobalt-60. The number identifying the isotope, known as the mass number, specifies how

many nucleons the atomic nucleus is composed of. For radiographic purposes, a stack of pellets of the isotope is sealed into a small steel container with a diameter of a few millimetres which is placed in a transport container shielding against radioactive radiation emerging from the isotope. An example of a portable transport container for Iridium-192 is shown in Figure 2.3. The shielding is usually lead- or depleted uranium-based and its thickness depends on the energy of the γ -rays emitted by the isotope. The container weight can be considerable in order to shield a high energetic source properly and may require a crane for positioning (approx. 20 kg for an Iridium-192 source and approx. 210 kg for a Cobalt-60 source). Therefore, a compromise between safety and weight needs to be made for sources of very large radiation strength [4].



Figure 2.3 *Photo of a portable transport container of a γ -ray source (a radiation tip and a collimator are mounted on the right of the container in order to control the spatial exposure intensity)*

Comparison between X-ray tubes and γ -ray sources

Apart from the emitted energy, there are important practical differences between X-ray tubes and γ -ray sources. X-ray tubes need a high voltage power supply and can be switched on and off as necessary. The voltage setting influences directly

the energy spectrum of the emitted X-rays. γ -ray sources radiate continuously with a constant and unchangeable energy spectrum, however, their activity reduces over time defined by the radioactive half-life of the isotope. Because γ -ray sources cannot be switched off, they need to be in a highly shielded container and both released and returned by a mechanical remote control. In the scenario where the remote control fails to return the isotope correctly in the container, it can be very challenging to remove the isotope without causing a considerable radiation dose (absorbed radiation energy per mass) to the operator. However, the ability to conduct radiographic inspections without an on-site power supply is an important advantage of a γ -ray source. Furthermore, when aiming to radiograph thick and dense objects, often it is only γ -sources which are practically able to provide sufficiently strong radiation to penetrate the object and generate an exposure in a reasonable amount of time. Comparing the dose rates (radiation energy dose per time) that are achievable with X-ray and γ -ray sources, it must be stated that X-ray sources achieve a 10 to 100 times higher dose rate in practice than comparable γ -ray sources.

Detectors

Apart from digital detectors such as imaging plates or Digital Detector Arrays, traditional analogue film is still very important and often used for industrial NDT. A big advantage of film is that the calibration effort necessary to set up a digital detector can be omitted. For many applications, it is also a cheaper option compared to an expensive digital detector and the resolution of film is higher compared to digital detectors. Furthermore, the flexibility of a film also has practical benefits. For example, it is possible to cover large areas of curved objects such as pipes by wrapping with film or achieving panoramic images in one shot. This is not possible with an inflexible digital detector of a limited recording field. It should also be highlighted that films were developed over a

century and that they are now well established for many decades whereas digital detectors are a more recent technological development. For many industries, especially also the nuclear industry which is particularly concerned with the safety of its facilities, films are considered a more conservative and reliable detector than digital alternatives. For them, films provide crucial advantages to digital alternatives. For example, it is possible to compare recent inspections directly with exposures made before digital alternatives were available and films can easily be archived for many decades as legally required.

During the conducted research work for this thesis, a particular interest in films has been developed. Therefore, this section concentrates on films rather than digital detectors.

Films

Radiographic NDT films consist of a transparent base made of polyester or Polyethylene Terephthalate (PET) with a thickness of 100 to 150 μm . The base is coated on both sides (to double the rate of exposure) with a radiation-sensitive film emulsion of 10 μm thickness [12]. The emulsion contains silver halide crystals that are sensitive to radiation. The silver halide crystals that are exposed by radiation are activated forming the so-called latent image on the exposed film. In the next step, the exposed film needs to be developed. During this process, the activated silver halide crystals are turned into metallic silver and the unexposed silver halide particles are washed off the film. Figure 2.4 shows an image of an exposed and developed film taken by an electron microscope at EDF. The developed silver particles forming clouds are clearly visible. The term “film system” describes the combination of the film and its processing such as the film development that is carried out according to the instructions provided by the manufacturers of the film and the processing chemicals [13]. The main difference

between films used in NDT and others for medical applications lies within the process of exposure. Both medical and photographic film are very light sensitive and light photons expose the film either directly (in photography) or indirectly using a scintillator screen that converts the X-rays into light. The latter is the case for the medical application. However, in NDT, intensifying screens are used that are placed in direct contact with the film. These screens are made of a thin lead sheet of 20 to 400 μm thickness, depending on the exposing energy. The exposing radiation generates photoelectrons in these screens and the film emulsion is subsequently exposed by these electrons rather than directly by the photons [12]. This approach necessarily intensifies the exposure because single photons can generate a cascade of exposing electrons. Without this, too little X- or γ -radiation would be absorbed by the film, making it unable to generate the latent image in a reasonable amount of exposure time.

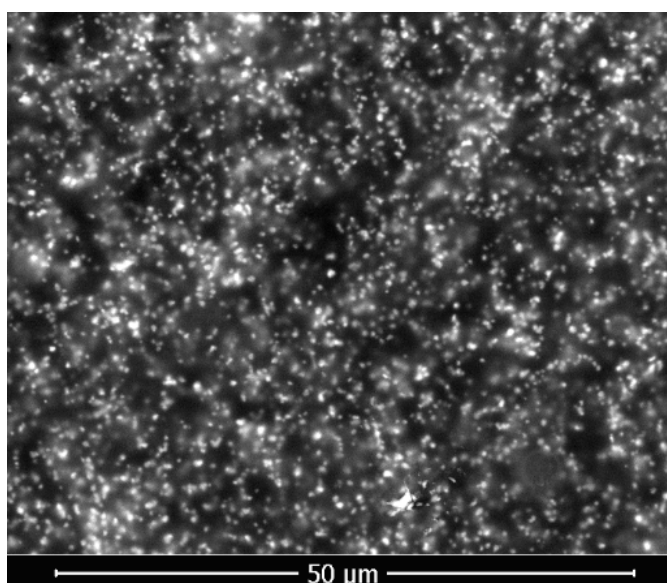


Figure 2.4 *Electron-microscopical image of an exposed and developed film with visible silver particles.*

The exposed and developed film exhibits a higher opacity against light in areas where it was initially exposed more intensively. That film blackening is caused by silver that obstructs the visible light and reduces the film transparency locally by reflection, diffraction, scattering and mainly absorption. Areas of the film that have been exposed more intensively appear darker because more film grains are developed. However, unexposed areas are not completely transparent but show an initial slight blackening because of the opacity of the film base and fog. The fog increases with the storage time of the film before it is purposely exposed and developed. It is caused by an incremental pre-exposure due to natural background radiation even if the film is well packed. Therefore, a film usually has a date of expiry, which indicates when the fog is no longer insignificant.

The opacity of a developed film is quantified by the concept of “visual diffuse Optical Density” (OD, ISO 5, parts 1–3 [14]–[16]). It represents a logarithmic ratio between the light incident on the film, illuminating it from the back side and the light transmitted through the film and reaching the eye of the investigator. The negative logarithm of the transmittance t specifies the Optical Density as

$$OD \equiv -\log_{10} t. \quad (2.3)$$

The transmittance t itself is defined as the ratio between the radiant flux transmitted Φ_e^t and the radiant flux received Φ_e^i by the film under viewing illumination [ISO 5-2:2009 [15]]

$$t \equiv \frac{\Phi_e^t}{\Phi_e^i}. \quad (2.4)$$

The exposed and developed film is examined on a film viewer, known as a radiographic illuminator or negatoscope, which illuminates the film from its back side with homogenous light to facilitate the interpretation. A fully exposed and so

fully saturated NDT film has an OD of more than 10 whereas a value of $OD = 0$ represents complete transparency. This is much higher than a medical film that saturates at an OD of around 4. The NDT film saturates only with a much higher exposure dose due to the silver content being much higher compared to medical films. However, the practical OD range in NDT varies only from 0 to 5. Otherwise, the opacity would be too high to produce good images on the film viewing box or the film would destruct by “grilling” due to a huge amount of light necessary for sufficient transmission; almost all of this light would be absorbed by the emulsion layers. Unlike medical films, NDT films unveil a linear response between exposure and OD within the practical OD range [12].

2.2 2D Fourier transform

Main parts of the work presented in this thesis are related to image processing tasks. Probably the most important mathematical tool within the field of image processing, or signal processing in general, is the Fourier transform, which will be introduced here. It was shown by the French mathematician and physicist Jean Baptiste Joseph Fourier in 1822 [17] that a periodic function can be represented fully by a sum of trigonometric functions through the Fourier transform. The Fourier transform is an integral transform that can be applied to one- or higher-dimensional signals in the original domain leading to a full representation of that signal in a complex formulation in the frequency domain by a specific amplitude and phase spectrum. The original domain for time-varying one-dimensional signals is typically the time domain or for two-dimensional signals such as images, the original domain is called spatial domain. The reader might be familiar with traditional signal processing tasks where the signal is time-dependent and, therefore, the Fourier spectrum of that signal delivers

information about the signal's frequency and phase information. Phase and frequency are then always referred to time shifts (phase) and cycles per time (frequency). In image processing, the signal varies within space rather than within time resulting in a spatial frequency spectrum (cycles per space) and spatial signal shifts (phase) spectrum.

Particularly, the discrete Fourier transform in two dimensions (2D DFT) is crucial for the presented work. The 2D DFT is probably the most important tool in image processing. It enables to filter the image efficiently in the Fourier domain, which refers to the complex frequency domain, by modifying the image spectra rather than processing the original image itself. A grey-value digital image is a two-dimensional set of discrete samples defined by pixel values. The image can be represented by an m by n matrix $\mathbf{X}$. The 2D DFT of that image matrix is defined as [18]

$$Y_{p,q} = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} X_{j,k} e^{-2\pi i \frac{jp}{m}} e^{-2\pi i \frac{kq}{n}} \quad (2.5)$$

with i as the unit imaginary number and the indices p, j and q, k respectively run from 0 to $m - 1$ and from 0 to $n - 1$ respectively. The resulting spectrum matrix $\mathbf{Y}$ is complex-valued and can be split into an amplitude spectrum $|\mathbf{Y}|$ and a phase spectrum $\arg(\mathbf{Y})$, where $|\cdot|$ denotes the modulus (magnitude) and $\arg(\cdot)$ denotes the argument (phase) of a complex number.

The one-dimensional case for a time-varying signal is first regarded to demonstrate the interpretation of the spectra. The amplitude spectrum contains information about the magnitude of the signals' underlying harmonic functions after decomposition in trigonometric functions of specific frequencies. The phase spectrum contains the phase angle or phase shift information of the complex-valued and transformed signal. The phase shift is defined in reference to the time

0 in the case for time-varying signals. For space varying signals, the phase shift is usually defined in reference to the centre or origin of the image. Therefore, combining magnitude and phase spectrum, it is known the amount of the harmonic components (magnitude) and the time delay (phase) of their appearance in the original signal. These two components entirely represent the original signal and equal it when inversely transformed. Figure 2.5 shows a sine wave signal in the time domain (top part) and its magnitude spectrum in the frequency domain (bottom part). The peak in the spectrum indicates the frequency of the sine signal in the time domain.

When the 2D DFT is applied to two-dimensional (2D) signals such as images, the 2D spatial frequency spectrum as well as the 2D spatial phase spectrum are calculated: the first describes the spatial periodicity of the image in terms of harmonics and the latter the local appearance of image texture components. Together, the two spectra represent the image totally in the spectral domain. Figure 2.6 shows on the left three cases of a sine wave propagating along the vertical axis in the spatial domain. Its frequency spectrum is calculated by the magnitude of the 2D DFT and plotted on the right of Figure 2.6. Three different frequency cases are shown with an increasing frequency from the top to the bottom of the figure. The points in the frequency spectra are analogous to the frequency peak in the one-dimensional case. As the frequency increases, the points tend towards the edges of the spectrum because higher frequencies are located closer to the edges in the two-dimensional spectrum. By definition, the centre of the spectrum represents the frequency 0.

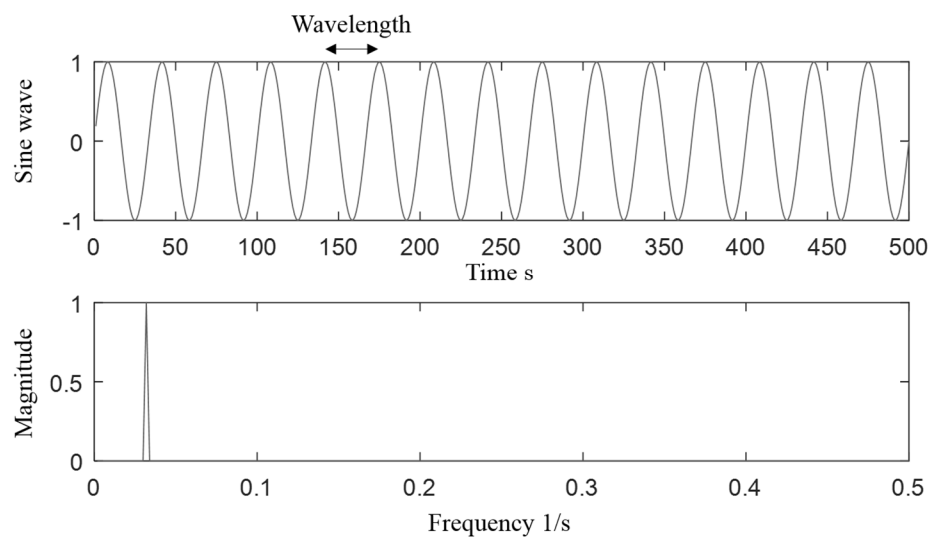


Figure 2.5 *1D sine wave signal in the time domain (top) and associated frequency spectrum in the frequency domain (bottom)*

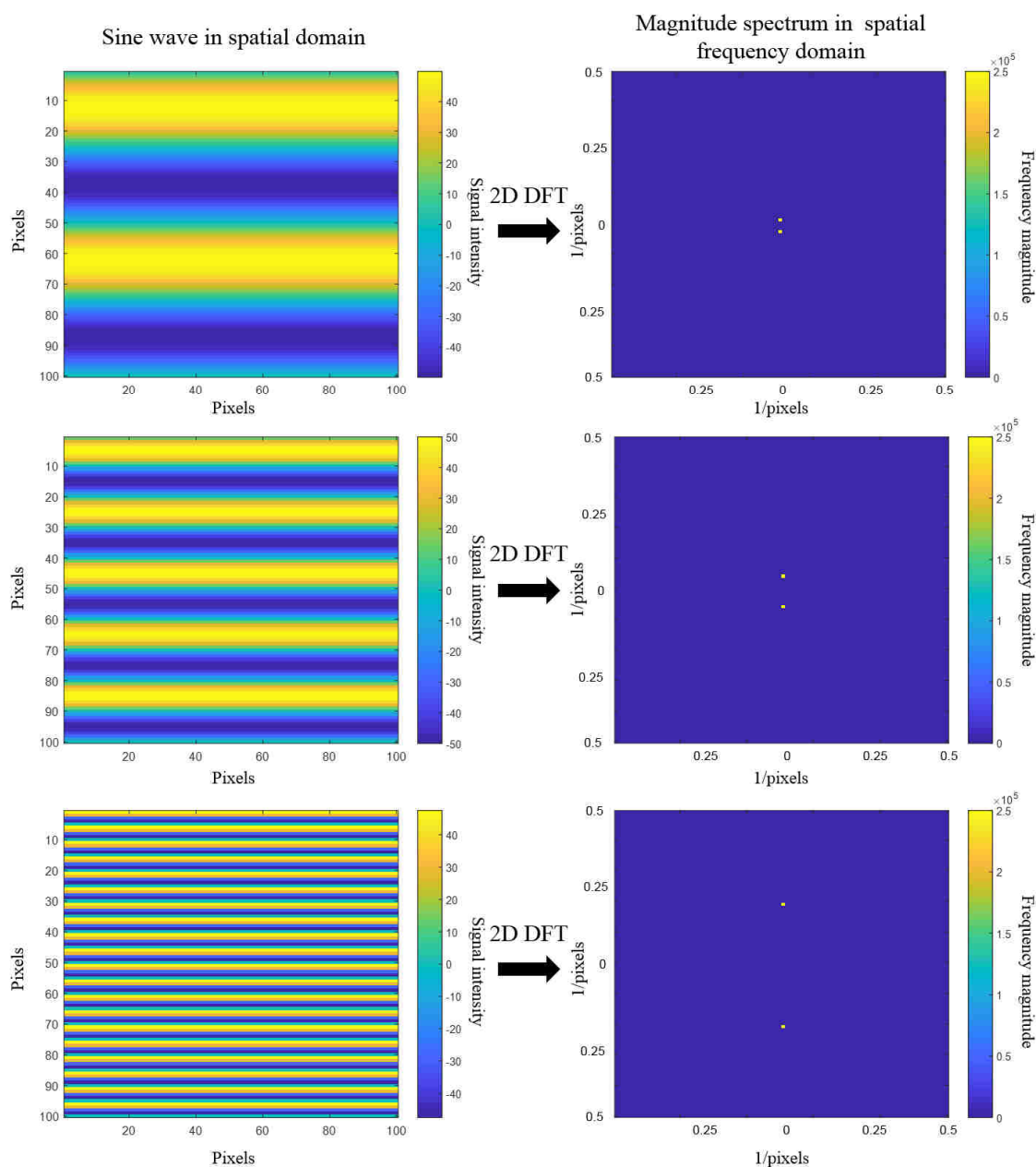


Figure 2.6 *Sine wave along the vertical axis in a two-dimensional image (left) and its frequency spectrum (right) with increasing frequency of the sine wave from the top to the bottom*

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

In this chapter, a new visibility criterion, originally established in the medical field, is introduced, implemented and validated for application within Industrial Radiology.

The chapter starts with an introduction explaining the motivation of why quantitative visibility criteria are vital for advanced radiographic setup planning and test procedure qualification when using computer simulations. This introduction will be followed by a presentation of the currently available visibility criteria in NDE, stating their drawbacks and emphasising the need for a better criterion. As such, the Channelized Hotelling Observer, from the medical field, is then outlined, which has good potential for applications in NDE. This is highlighted by the results and validation sections that follow. The last section of this chapter consists of concluding remarks.

The work presented in this chapter is published in NDT & E International [7] and the chapter follows the structure of the published paper.

3.1 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 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 visual 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.

The interpretation of a radiographic 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 the work presented in this chapter 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 from the methods currently used in NDE. This new method will improve the process of qualifying test procedures and allows the best radiographic test setup with regard to visibility to be found.

This chapter 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.

3.2 State of the art

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

3.2.1 Rose model

In the 1940s, the American physicist Albert Rose worked as a pioneer in investigating the human ability to detect circular visual signals in uniform noise. He assumed an analogy, namely that the visual process is just based on counting light quanta by all kind of image devices, as it could be electrical, like a television tube, chemical, as a photographic film, or biological, as the human eye.

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 average number of absorbed photon quanta N_q depends on the standard deviation σ of the average of the absorbed quanta: the lower σ , the more likely N_q is close to the expected value. Or put another way, the lower σ is, the easier it is to distinguish smaller changes of N_q , referred to as ΔN_q , the smallest distinguishable change. This leads to the proportionality

$$\Delta N_q \propto \sigma. \quad (3.1)$$

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

$$\sigma \equiv \sqrt{\text{Var}(N_q)} = \sqrt{N_q} \quad (3.2)$$

with $\text{Var}(\quad)$ as the variance, it can be stated that

$$\Delta N_q \propto \sqrt{N_q} \quad (3.3)$$

or by introducing a proportionality factor k_R and rearranging

$$\frac{\Delta N_q}{\sqrt{N_q}} = k_R \quad (3.4)$$

which is called the Rose model representing a contrast-to-noise ratio. The factor k_R needs to be defined by visual experiments. These showed that a good approximated value of k_R should be around 5 to assure visibility. [19]–[21]

Introducing the scene brightness B_S as proportional to the number of photons N_q divided by the area under investigation with side length h_A , i.e.

$$B_S \propto \frac{N_q}{h_A^2} \quad (3.5)$$

and the threshold contrast C_t as (using equation (3.4))

$$C_t \equiv \frac{\Delta B_S}{B_S} = \frac{\Delta N_q}{N_q} = \frac{k_R}{\sqrt{N_q}} \quad (3.6)$$

where ΔB_S is the smallest distinguishable change of brightness in analogy to ΔN_q . Combining equations (3.5) and (3.6) leads to

$$B_S \propto \frac{1}{C_t^2 h_A^2} \quad (3.7)$$

or the so-called characteristic equation of any ideal image device's performance

$$B_S C_t^2 \alpha^2 = \text{const.} \quad (3.8)$$

where α is the angle at the lens, e.g. the angle at the eye, defined by the investigated length h_A . The investigated length and the viewing distance define the viewing angle α . Equation (3.8) defines a relationship between B_S , C_t and α such that if two of them are known, the other is uniquely defined. [19]–[21]

3.2.2 EDF criterion

This visibility measure was developed in 2003 by EDF and described in [22], [23]. 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 mm²; eccentricity: 0.89) around every pixel of the image. That elliptical area is assumed to be the detectability limit of a defect's extent: any further increase of the defect's area would not influence its visibility, thus any bigger defect should have the same visibility. Only smaller defects would be characterised by specific, distinguishable visibilities. However, the procedure of how the geometry of the

ellipse was defined empirically is not traceable or documented in the literature. The ellipse is rotated stepwise between 0° and 180° using a 22.5° increment as shown in Figure 3.1. The maximum of the average contrast values in any position of the ellipse is taken as the visibility value associated with 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. [22]–[24]

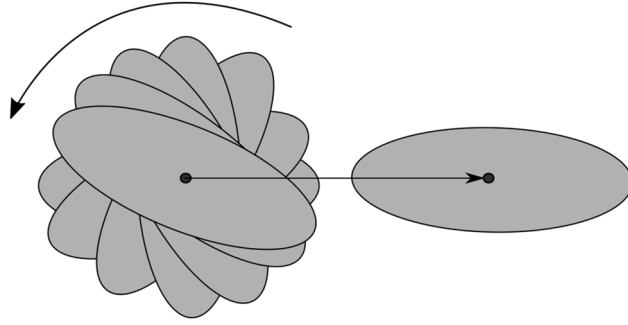


Figure 3.1 *Illustration of the rotation and displacement of the elliptical area around any pixel centre (black dot) used to define a dedicated contrast value to the specific pixel*

3.2.3 CEA criterion

The here so-called “CEA criterion” was established in 2016 by Tisseur *et al.* from the French research institution CEA in [25]. This criterion is based on the Rose model but generalises it beyond circular features by also considering elongated shapes. It rests on the industrial standard [26] giving a reference that elongated shapes of a specific width W should be distinguished by the same visibility as circular shapes of a diameter $\emptyset$ if it is given that

$$\emptyset = i_{CEA} W \quad (3.9)$$

where the shape factor $i_{CEA} = [2, 2.5]$ depends on the considered standard and is set to $i_{CEA} = 2.2$ in [25]. Elongated shapes are distinguished by their shape ratio

$$r_S = \frac{L_f}{W} \quad (3.10)$$

where L_f is the length of the flaw. An equivalent area A_{eq} for elongated shapes can then be derived by

$$A_{eq} = \frac{\pi(2.2 W)^2}{4} \approx 3.8 W^2 \quad (3.11)$$

and a maximal area is set to

$$A_{max} = \min(A_{eq}, 1.6 \text{ mm}^2) \quad (3.12)$$

defining a threshold of the visibility under the assumption that all flaws bigger than 1.6 mm^2 are characterised by the same visibility. The value of 1.6 mm^2 is taken from the EDF criterion described above. Also, the contrast C between flaw and background is needed that can be calculated by

$$C = |OD_{flaw} - OD_{bg}| \quad (3.13)$$

where $| \cdot |$ indicates the absolute value, OD_{flaw} is the Optical Density of the flaw and OD_{bg} of the background. The last necessary step is to describe the noise value: As for the other visibility models, Gaussian noise with a standard deviation of σ_D^{simu} is used to simulate the noise. Considering a pixel size l_{pix} and the minimal resolution of the eye l_{eye} the simulated visual noise in the eye σ_D^{eye} due to granularity is

$$\sigma_D^{eye} = \sigma_D^{simu} \frac{l_{pix}}{l_{eye}}. \quad (3.14)$$

Now the final visibility indicator I_{CEA} used to measure the visibility of a flaw is

$$I_{CEA} \equiv \frac{C}{\sigma_D^{eye}} \sqrt{A_{max}}. \quad (3.15)$$

3.2.4 INSA criterion

Kaftandjian *et al.* from the French Grande École INSA Lyon proposed in 2016 another criterion based on the Rose approach, published in [27], and called here as “INSA criterion”. The 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 where it is introduced as a penalty factor to decrease the gross result of Rose’s model. The gradient is defined as the maximal greyscale level difference d_{GL} measured in the neighbourhood around the defect. That neighbourhood is defined as a six pixel wide band located three pixels far from the actual flaw location. Thus the INSA criterion is defined as

$$I_{INSA} \equiv \frac{C}{\sigma} \frac{\sqrt{A_d}}{\sqrt{(1 + \frac{d_{GL}}{GL_{max}})}} \quad (3.16)$$

where C is the contrast between flaw signal and background, σ describes the image noise, A_d is the area of the defect and GL_{max} is the maximal greyscale level. Once more, the defect area is also limited to 1.6 mm² as defined by the EDF criterion.

3.2.5 CSF criterion

A totally different criterion is not based on Rose’s approach but on the contrast sensitivity of the human eye [24]. The Contrast Sensitivity Function (CSF) describes how the human eye is sensitive to a visual signal in dependence of its contrast and spatial frequency [28], [29]. It is a well-established fact that the

human eye can identify best a low contrast visual signal if its spatial frequency is around two to five cycles per degree of viewing angle. A strong decrease of visibility as a function of contrast can be stated out of that range to lower or higher spatial frequencies [28], [29].

To apply that criterion, 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.

3.2.6 Discussion of existing criteria

The gradient of Optical Density that surrounds the defect is not considered in the Rose model nor is it in the EDF, the CEA or the CSF criterion. Only the INSA criterion considers that gradient. However, the INSA criterion lacks a well-founded theoretical or bibliographical justification for it. Regarding the defect geometry, it can be stated that the Rose model, as well as the INSA criterion, are only defined for circular flaws and not for elongated defects. The EDF criterion also lacks a theoretical explanation as to why the regarded geometry of the ellipse would define the detectability limit. The CSF criterion takes into account the contrast sensitivity of the human eye. However, it does not take into account the image gradient [24].

There is a need to overcome these issues in industry and the development of a more general and theoretically as well as bibliographically well-founded visibility model is required. Therefore, the first main part of this thesis is the presentation of a new visibility model in the next sections of this chapter. This new model is more general than the presented models and overcomes the described issues.

3.3 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 flaw 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. In the literature, the development of so-called Model Observers has advanced significantly during the last decades. Image quality is defined as how well desired information can be extracted from an image [30], generally by an observer. Model Observers (MOs) 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. Psychophysical experiments are visual tasks with humans to analyse the real human behaviour in visual detection. 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. [30]

Considering different kinds of possible detection tasks and many different observer models described in the literature, Eckstein *et al.* [31] recommend as a first step to define the task under investigation and to choose an appropriate MO. Examples of visual tasks could be to decide whether a flaw signal is present or absent. That task resulting in a yes/no decision is called "binary classification". Another task can be to classify the image in a number of different categories, identifying if the flaw signal is very well or less well visible. A third

example of a task is the Multiple-Alternative Forced Choice task (MAFC). Here, is the flaw signal always present but the observer shall decide in which pre-defined possible locations it is. Having selected an appropriate task, the flaw signals and background should be selected as well, in order to simulate real tasks. Then an appropriate MO can be chosen that measures the visibility of the flaw signal embedded in visual noise. Usually, the MOs are based on a linear decision strategy making use of statistical knowledge about both the flaw signal and the background. [31]

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

3.3.1 Theory and definitions

The process of imaging an object can be described by

$$\mathcal{H}(\mathbf{f}) + \mathbf{n} = \mathbf{g} \quad (3.17)$$

where $\mathbf{f}$ denotes the object being imaged, $\mathcal{H}$ the imaging function representing the imaging system, $\mathbf{n}$ the noise generated during the measurement and $\mathbf{g}$ the image [32]. 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. This simple reordering can be illustrated by

$$\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{pmatrix} \rightarrow \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{pmatrix}. \quad (3.18)$$

If the task is one of flaw signal detection resulting in a yes/no decision (binary classification), the observer should be capable of categorising the image under investigation into one of just two specific classes. In this case of a binary problem, the classes are “signal-present” containing images with a visual signal signature and “signal-absent” containing images without the visual signal of interest. [30], [33]

If the observer hypothesises (hypothesis h_1) that the image contains a background $\mathbf{b}$, noise $\mathbf{n}$ and the flaw signal $\mathbf{s}$ thus

$$\mathbf{g}(h_1) = \mathbf{b} + \mathbf{n} + \mathbf{s}. \quad (3.19)$$

Otherwise, it hypothesises (hypothesis h_2) that the image consists only of background and noise

$$\mathbf{g}(h_2) = \mathbf{b} + \mathbf{n}. \quad (3.20)$$

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 [30], [31], [33]. Figure 3.2 describes schematically the image production and decision process.

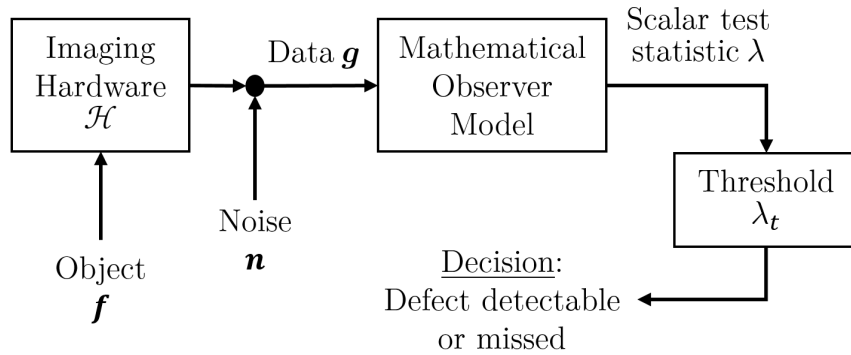


Figure 3.2 Flow chart illustrating the decision process of a Model Observer [34]

The key question is how the observer computes the test statistic. The work presented in this chapter is restricted to linear observers, which compute the test statistic by creating a weighted total of the image's intensities at all pixel points [33]

$$\lambda = \sum_{j=0}^{M-1} [\mathbf{w}]_j [\mathbf{g}]_j = \mathbf{w} \cdot \mathbf{g} \quad (3.21)$$

where M denotes the total pixel number, j is an index variable indicating a specific cell value of the vectors and $\mathbf{w}$ is the weighting vector called “observer template” [33].

In a simplistic case, the MO just uses an expected approximation of the flaw signal as the observer template and takes the scalar product with the image under investigation [35]. The template is obtained by observer training, considering a set of images containing similar flaw signals and another set of images without the flaw signal. The difference between the means of the image sets is the template to which the observer was trained. Furthermore, the scalar product indicates how likely it is that the investigated image contains the flaw signal: it is more likely if the resulting value becomes higher and vice versa. That simplistic MO can be summarised as

$$\lambda = (\bar{\mathbf{g}}_1 - \bar{\mathbf{g}}_2)^{\text{tr}} \mathbf{g} \quad (3.22)$$

where $(\)^{\text{tr}}$ denotes the transpose and $\bar{(\)}$ denotes the mean value of a set (population) of images $\bar{\mathbf{g}}_1$ containing the flaw signal and a set of images $\bar{\mathbf{g}}_2$ without the flaw signal. [35]

Furthermore, two statistical properties are of interest [33]. The first is the already mentioned image mean $\bar{\mathbf{g}}$ and the second is the covariance matrix $\mathbf{K}$ defined as

$$\mathbf{K} \equiv \langle (\mathbf{g} - \bar{\mathbf{g}})(\mathbf{g} - \bar{\mathbf{g}})^{\text{tr}} \rangle \quad (3.23)$$

where the angle brackets denote the ensemble average. The covariance can be illustrated as a measure of intensity change between two pixels of the same image regarding all images in a population of images: it represents a measure of the correlation between any two pixels across a population of images. This information can be known *a priori* if available, else it needs to be estimated. [33]

For illustration, the covariance between two pixels x_i and x_j denoted as $\text{Cov}(x_i, x_j)$ is defined as

$$\begin{aligned} \text{Cov}(x_i, x_j) &\equiv \text{E}[(x_i - \text{E}(x_i)) \cdot (x_j - \text{E}(x_j))] \hat{=} \\ &\hat{=} \frac{\sum_{k=1}^{N_s} ([x_i]_k - \bar{x}_i)([x_j]_k - \bar{x}_j)}{N_s} \end{aligned} \quad (3.24)$$

where $\text{E}()$ describes the expectation value and N_s is the number of samples in the population. The full covariance information of an image represented by an M dimensional vector can be stored in an M^2 dimensional matrix.

After Bochud *et al.* [36], the statistical properties are completely known in the case of well-defined computer-generated background. So the covariance is calculable instead of being estimated using a population of images. In the circumstances of the work presented here, the statistical properties of the simulated images are not known *a priori*: a Monte-Carlo based simulation process combined with a noise model representing the film graininess is used here, and is sufficiently sophisticated that a conclusion about the image's covariance matrix needs to be derived from a population of images. The significant challenge is that an invertible estimation of the covariance matrix needs a population at least as

big as the dimension of the covariance matrix to be estimated [37]. In the case of high-resolution images represented by vectors having the dimension of the number of pixels (typically millions) in the image, it would mean that a huge population of high-resolution images is necessary; even with modern computer capabilities this is not feasible.

3.3.2 Hotelling Observer

The Hotelling Observer is based on the Hotelling Trace Criterion [38] named after the American statistician Harold Hotelling (1895–1973). That criterion measures the separability between two classes, e. g. flaw signal-present/absent. If it is assumed in the binary problem case that the covariance matrices are similar for the signal present and absent case and that the image covariance matrix is regular, then the Hotelling Observer’s test statistic is given as [30], [34]

$$\lambda_{Hot}(\mathbf{g}) \equiv \mathbf{s}^{\text{tr}} \mathbf{K}^{-1} \mathbf{g} \quad (3.25)$$

with the flaw signal $\mathbf{s} = \overline{\mathbf{g}}_2 - \overline{\mathbf{g}}_1$.

This kind of observer is called a Prewhitening Matched Filter (PMF) because the application of $\mathbf{K}^{-1}$ on $\mathbf{g}$ leads to a decorrelation in $\mathbf{g}$, and the product between $\mathbf{s}$ and $\mathbf{g}$ is called a “matched filtering” operation [30]. The difficulty here is to estimate the covariance matrix as mentioned before: in order for the covariance matrix to remain invertible, the number of images in the population has to be larger than the number of pixels in the image thereby the covariance becomes invertible. A convergence study with a small $10 \cdot 10$ pixel image even showed that the detectability measure only converges when the population considerably exceeds the number of pixels. This is illustrated by Figure 3.3: as the population exceeds the number of pixels, in that case 100, the MO’s output starts to

converge. The peak is located at a population size of 100 because this is the number of pixels in the image. It should be highlighted that the indicated visibility measure on the vertical axis is only a theoretical measure. The actual visibility is to be taken from the converged area exceeding a population size of around 200. Independently of the image size, it is advisable to calculate the covariance matrix using a population size at least twice as big as the number of pixels in the image to receive a converged measure. The values for a population number less than 100 could only be calculated using the pseudo-inverse of $\mathbf{K}$. To avoid that issue, it is possible to use a non-prewhitening observer that does not need $\mathbf{K}^{-1}$, but this would lead to a worse performance [30].

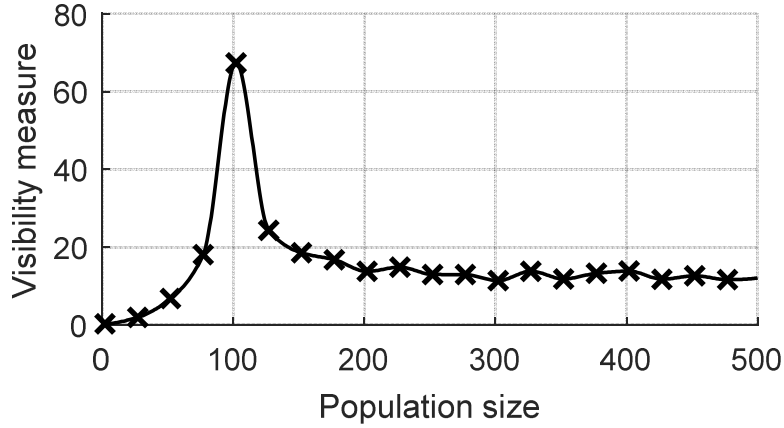


Figure 3.3 *Convergence study of the detectability measure in relation to the population size for a 10 · 10 pixel image including an interpolation*

3.3.3 Channelized Hotelling Observer

A possibility to reduce the problem's dimension is to advance to the Channelized Hotelling Observer (CHO) incorporating frequency or orientation selective channels [39]. The CHO can be built up in a more anthropomorphic way as frequency or orientation selectivity are a known characteristic of the human

visual system [33]. The image is preprocessed by filtering through channels that are adjusted to specific special frequencies or orientations [31]. It is also possible to link the CHO with the human eye's contrast-frequency sensitivity by application of channels tuned to the CSF. Thus, the frequency selective channels of number N_C are applied to the image in the spatial-frequency domain either in an consecutive, non-overlapping [39]–[41] or in an overlapping manner [41]. The channels reduce the high dimensional image vector to a set of channel-responses by integrating the image information over the frequencies defined by the channel filter [33]. That integration is carried out by a scalar product between a filter vector defining the channel in the frequency domain, usually a band-pass filter, and the Fourier transformed image $\mathbf{g}$ [33]:

$$\mathbf{u} \equiv \mathbf{T}^{\text{tr}} \mathbf{g} \quad (3.26)$$

where $\mathbf{T}$ is an $M \cdot N_C$ dimensional matrix representing the bank of channel filters in its columns and $\mathbf{u}$ is the N_C dimensional channel response. The problem's dimension will be reduced hugely if $N_C \ll M$, as would usually be the case [32], [37].

If the Hotelling Observer is operating on the channelized image $\mathbf{u}$, the test statistic of the CHO is given by [40]

$$\lambda_{CHO}(\mathbf{g}) \equiv \mathbf{T} \mathbf{s}^{\text{tr}} \mathbf{K}_{CHO}^{-1} \mathbf{u} \quad (3.27)$$

where $\mathbf{K}_{CHO}$ is the covariance matrix of the channel response and $\mathbf{s}$ is the Fourier transformed flaw signal $\mathbf{s}$.

Various filter functions are used for the channel definition, such as constant functions (called constant-Q filters) [39] or Difference-Of-Gaussians profiles [41] that are defined to be rotationally symmetric in the spatial frequency domain.

The next paragraph describes the definition of the mentioned constant-Q filters.

3.3.1. Constant-Q filters

After Myers and Barrett [39], the constant-Q filters are defined as rectangular, nonoverlapping channels in the frequency domain. The matrix T filters all spatial frequencies ρ of the image under investigation. If L describes the number of used filters and $m = 1, 2, \dots, L$ then T stacks the different channels that are defined as

$$T_m(\rho) = \begin{cases} 0 & \text{for } \rho \leq Q^{m-1}\rho_c \\ 1 & \text{for } Q^{m-1}\rho_c < \rho < Q^m\rho_c \\ 0 & \text{for } \rho \geq Q^m\rho_c \end{cases} \quad (3.28)$$

where the filter-width ratio Q and the cut-off frequency ρ_c are parameters defining the borders of the frequency passing the filter m . [39]

Figure 3.4 shows exemplarily the definition of the constant-Q channels in the frequency domain. The constant-Q channels are straightforward to implement and therefore a good candidate to choose for the CHO implementation described in this thesis. They also have been proven to provide better results than other filters for visibility tasks dealt with in NDT. This justifies the use of this specific kind of filters for the results presented in the next sections.

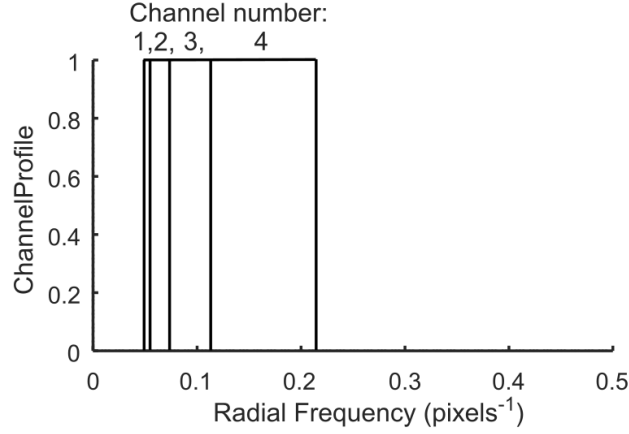


Figure 3.4 *Example of four ($m = 1, 2, 3, 4$) constant- Q filters displayed in the spatial frequency domain with channel parameters set to $\rho_c = 0.015$ and $Q = 2$ [41]*

3.4 Results

To validate the CHO in NDE, it is necessary to show the ability of the CHO to predict the defect's visibility. The validation was performed using different kinds of references: an industrial standard describing the visibility in X-ray NDE and two psychophysical datasets. In this work, radiographic simulation and setup modelling are performed by the simulation package MODERATO [6]. The simulated radiographs that are used to validate the model have been provided by EDF.

3.4.1 Validation by referring to standardised IQI visibility and comparison with existing visibility models

The first phase of validation is based on a comparison of the CHO result to an established industrial standard and comparison with other visibility models. Simulated images of different kinds of Image Quality Indicators (IQI) have been

considered. An IQI is usually taped to the object and both are X-rayed together. An IQI set consists of indicators having different diameters and geometries such as wire or steps and holes. By assessing which indicator of a specific diameter is at the limit of visibility, the quality of the radiograph in terms of visibility can be defined. Both wire and hole IQIs of different diameters have been X-rayed by simulation. Figure 3.5 shows wire and hole IQIs as well as radiographic simulations of a hole and a wire. The basis for validation is given by an industrial standard [26] describing a relationship between the visibility of a hole IQI and a wire IQI. Specifically, it provides a basis which allows one to state that a hole of a specific diameter provides the same visibility as a wire of another specific diameter.

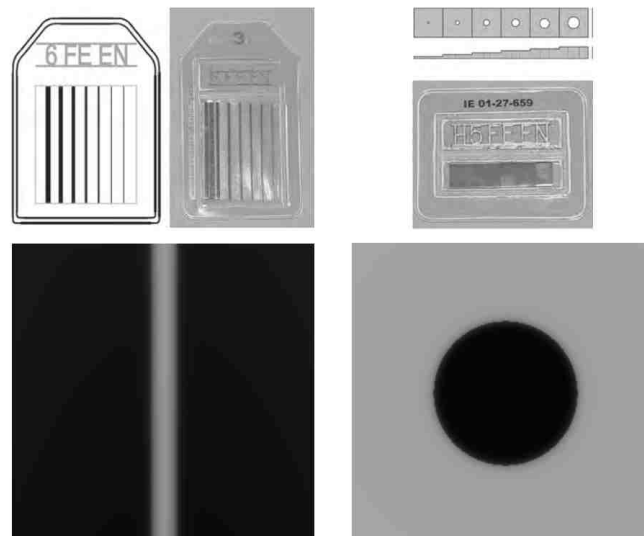


Figure 3.5 *Left part: Wire IQI (top) and simulated radiograph of a wire (bottom); Right part: Step hole IQI (top) and simulated radiograph of a hole (bottom). The shown simulated images are noiseless. Top images are used with permission of CRC Press, from Handbook of X-ray Imaging: Physics and Technology, 1st Edition, 2018; permission conveyed through Copyright Clearance Center, Inc.*

Configuration	Hole IQI	Wire IQI
number	diameter in	diameter in
	mm	mm
1	0.25	0.1
2	0.32	0.125
3	0.4	0.16
4	0.5	0.2
5	0.63	0.25
6	0.8	0.32
7	1	0.4
8	1.25	0.5

Table 3.1 *Considered diameters of hole and wire IQIs*

The different hole and wire IQI diameters considered in the image simulation are summarised by Table 3.1. Any pair of hole and wire geometry listed in the same row of Table 3.1 should be characterised by the same visibility after [26]. It is worth mentioning that wires of different length have been used in the present work, namely 10, 25 and 50 mm, as the standard [26] does not specify the wire length. The standard does not reference any literature describing how it was

determined that the IQIs in the same row would have the same visibility, which is not evident.

To test the model, firstly, noise is added to the noiseless high-resolution images ($6000 \cdot 1200$ pixels for the wire and $1200 \cdot 1200$ pixels for the hole; the wire images need to be bigger because of the length of the wires but the pixel size remains unchanged) with a 16-bit greyscale. Noise creation is undertaken using the same procedure as described in [42] using [43], allowing to build up a population of images and to enable the covariance matrix to be estimated. Normally distributed noise is added to any pixel of the image with a standard deviation σ_{noise} of

$$\sigma_{noise} = \sigma_{film} \sqrt{\frac{\pi \cdot 10^4}{4 \cdot A_p}} \cdot \sqrt{\frac{OD}{2}} \quad (3.29)$$

where A_p is the pixel area in μm^2 , OD is the Optical Density of the specific pixel and σ_{film} is an experimental value obtained by measuring the noise of real films, see [13]. The noise generated by this model does not simulate grain clusters by considering a correlation between pixels and overestimates the noise at small pixel sizes. These shortcomings can be overcome by the new noise model described in Chapter 4.

CHO using constant-Q filters

A routine has been written to calculate the test statistic by a CHO with constant-Q filters. Input parameters for these filters are the numbers of applied channels L , the filter-width ratio Q and the cut-off frequency ρ_c . It seemed reasonable to set $Q = 2.0$ as in [41]. The cut-off frequency was chosen to be $\rho_c = 0.03$ to also incorporate small spatial frequencies. Five channels have been used ($L = 5$), which is a reasonable size comparable to [41] and [44]. It seemed sensible

to use these parameter settings because they have been proven in the literature to deliver good results. It can also be stated that the results generated in this thesis are robust to small parameter changes. An additional channel has been added that takes into account very low frequencies from $\rho_c = 0$ to $\rho_c = 0.03$. This supplementary channel is necessary because the highest content of information in the spatial frequency domain is located close to the centre ($\rho_c = 0$) for all investigated images. The population size was set to $N_s = 600$ so that the results are reasonably converged and smooth. The process was run four times and the results averaged to improve the accuracy. The pixel area is set to $A_p = 10 \cdot 10 \mu\text{m}^2$ and $\sigma_{film} = 0.017$ at $OD = 2$ and the results are presented in Figure 3.6.

The MO would be totally consistent with [26] if the two curves for wire and hole IQI visibility were matching for all investigated configurations. It is notable that the CHO result diverges for higher diameters, but up to configuration number 4 (hole and wire diameter of 0.8 and 0.32 mm respectively), the CHO results match well with the validation basis given by [26]. A possible explanation for the deviation for higher diameters can be the increase of the defect area: the area of a hole increases with a power of 2 whereas the area of the wire increases only to the power of 1 with increasing diameter.

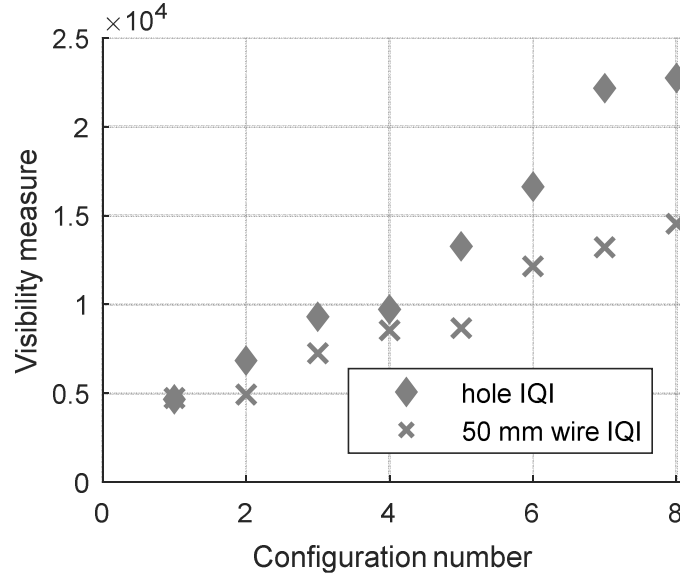


Figure 3.6 CHO result using constant- Q filters comparing the visibility of the hole IQI with the wire IQI of 50 mm length

Comparison of the CHO model with existing visibility models

It is interesting to perform a comparison of the new CHO visibility model with those already used by industry. The visibility results of these models, namely the EDF, CEA, INSA and CSF criterion are shown in Figure 3.7 after application to the simulated radiographic images containing the hole IQI and wire IQI. Any of the four subplots shows how the visibility measure given by the indicated visibility model changes with increasing IQI dimensions. In the perfect case of total accordance of the visibility model with the validation basis [26], the resulting curves for the hole respectively wire IQI would match completely. The same parameters as for the application of the CHO model have been used, namely a pixel area of $A_p = 10 \cdot 10 \mu\text{m}^2$ and the same film characteristic $\sigma_{film} = 0.017$ at $OD = 2$. These are the input parameters for the noise model. Overall the visibility models, the most promising results were achieved by investigating the wire IQI of 50 mm length, but the wire length only significantly influences the CSF criterion. All existing criteria result in an increasing divergence for

configurations with larger IQI diameters compared to [26] as is also the case for the implemented CHO. But it can be stated that the divergence is clearly weaker in the case of the CHO when compared to the existing models. The divergence can be visualised by the percentage divergence between the visibility results of the wire and hole IQI in comparison to [26]. The integrated percentage divergence between all investigated indicators is traced in Figure 3.8 for the case of the 25 mm wire IQI as well in Figure 3.9 for the case of the 50 mm wire IQI. In these figures, a lower value means that the visibility of both IQIs matches on average better for all investigated configurations after [26]. It can be clearly stated that the CHO with constant-Q filters reflects better the comparability between wire and hole IQI than it is the case for all other existing models. Thus the CHO model delivers a better visibility measure than the existing models currently considered in industry. However, it should be highlighted that this validation assumes the correctness of [26].

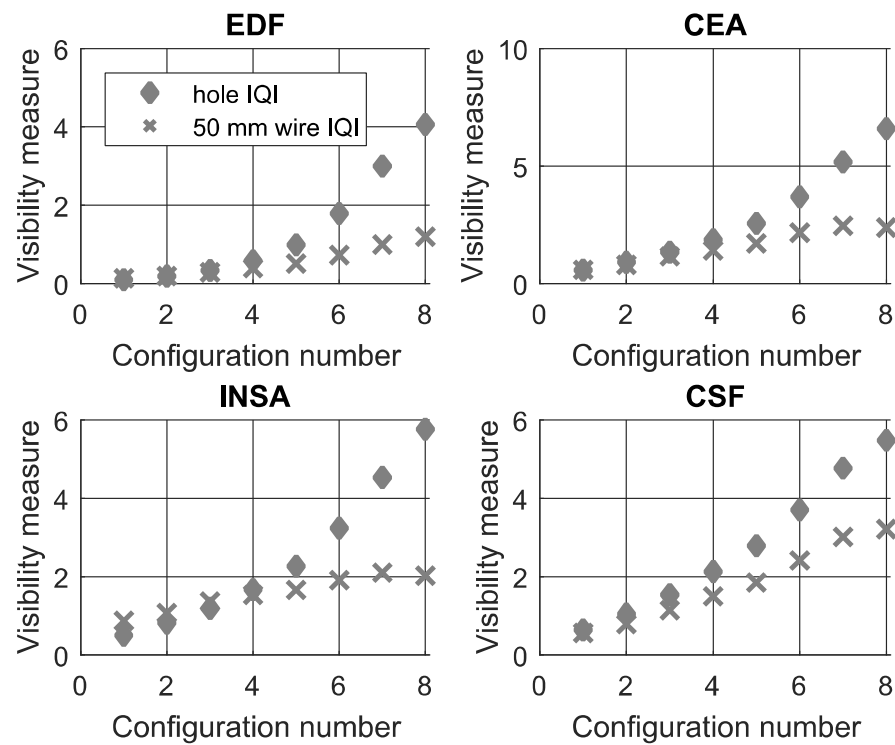


Figure 3.7 EDF, CEA, INSA and CSF criterion results comparing the visibility of the hole IQI with the wire IQI of 50 mm length

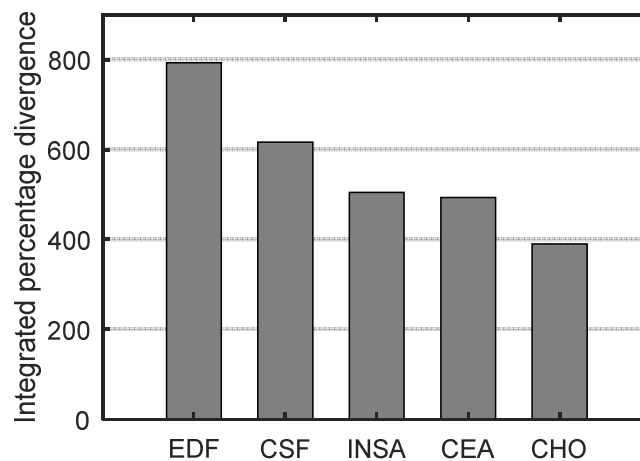


Figure 3.8 Integrated percentage divergence between visibility models and [9] of all configurations (wire IQI of 25 mm length)

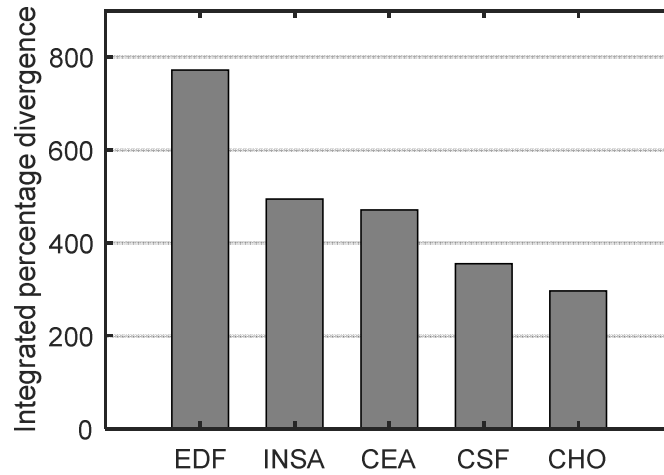


Figure 3.9 *Integrated percentage divergence between visibility models and [9] of all configurations (wire IQI of 50 mm length)*

3.4.2 Validation by dataset using elongated shaped visual signals

This validation is based on the psychophysical dataset described in [27]. A radiograph was produced consisting of a high number of visual defect signals. These signals were gained by performing an X-ray of 192 objects taped to a quadratic steel plate of 30 cm edge length and 30 mm thickness. The objects are of different longitudinal shape (diameter of 0.05 to 3.2 mm and length from 5 to 20 mm) and materials (copper, iron, lead and tungsten). The objects' attenuation was between 0.7 % and 7 % of the steel plate's background attenuation and the objects' position was randomly chosen on the source side with an orientation in respect to the steel plate of 0°, 45° and 90°.

The radiograph was evaluated by three trained experts (level 2 according to EN 473) ranking the visibility of every object. They were allowed to rank an object in an integer range of 0 to 4, respectively as invisible, very low, low, rather

high or highly visible and their rankings were averaged for every object. Radiographic images of all objects were separately simulated with a pixel area of $A_p = 10 \cdot 10 \mu\text{m}^2$ using the same setup. The film characteristic was set to $\sigma_{film} = 0.017$ at $OD = 2$. Afterwards, the simulated images were processed by the MO. The CHO parameters were unchanged to the description above. Only the population size was decreased to $N_s = 300$ because of the big dataset. A drawback of this decreased population size is the high standard deviation of 21.6 % when averaged over 4 calculations. The results are presented in Figure 3.10, plotting the CHO's results against the human assessments. Each point represents one object's visibility. The scattering of the measurements is caused by the human-based nature of the experiment: visibility is a subjective measure leading to scattered results when averaged over a limited number of human assessors.

A good correlation between the human and the simulated visibility assessment by the CHO is observable. Additionally, an envelope around the result is remarkable: an important result showing that the MO is able to clearly separate between very low and highly visible. Another very good result is that the MO did not lead to false negative results, which would be located in the lower-right part of the graph. False negative results mean that the MO was not able to warn of an actually well-visible and so important defect. However, that area of the graph is empty, which is very promising.

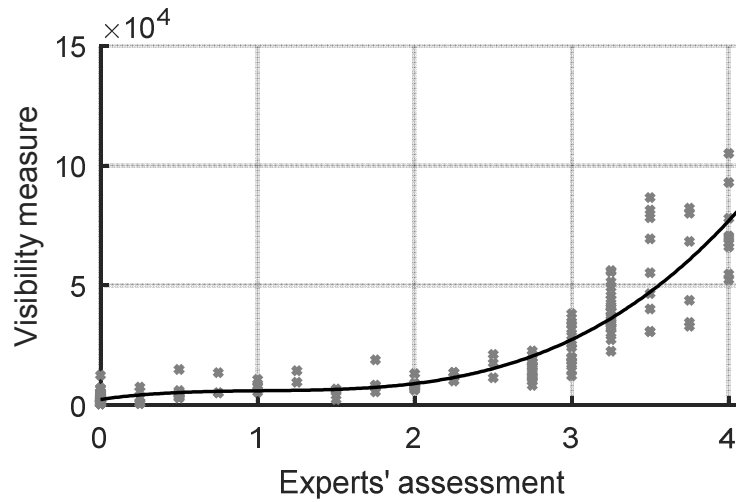


Figure 3.10 *Validation of CHO visibility measure by dataset using wire shaped defects including cubic fit*

3.4.3 Validation by dataset using circular shaped visual signals

Furthermore, circular shaped visual flaw signals were investigated and the MO's results were compared to a human assessment of simulated images displayed on a computer screen. In that case, the three assessors were untrained but familiar with industrial radiology. While it would be ideal to utilise trained experts for this and match the data used before (taken from previous work [27]), unfortunately, such a panel was unavailable for this study. A correlation between the visibility as assessed by the untrained panel and the detectability measures would still be expected, although it is expected that the untrained panel would generally be worse at detecting less visible defects.

The investigated setup is a socket weld connecting two pipes of different diameters and described in [27]. 81 configurations were generated with variation of the source position, detector orientation, pipe diameters and the geometrical

parameters of the notch representing the defect. Each configuration was simulated with and without the defect and randomly presented to the human assessors to ensure that they are unaware *a priori* if a defect is present. Radiographic images were simulated with a pixel area of $A_p = 80 \cdot 80 \mu\text{m}^2$ and the film characteristic $\sigma_{film} = 0.017$ was chosen. The human assessors were allowed to rate the defects' visibility in an integer range from 0 to 4 as before.

The CHO parameters were unchanged to the description above including the population size of $N_s = 300$. Every image was processed by the CHO three times and the results were averaged. The standard deviation of the results is 5.27 %, thus lower than for the dataset of elongated defect shapes. This can be explained by the noise model, which leads to a much lower noise amplitude for the increased pixel area. The results are presented in Figure 3.11, plotting the MO's results against the human assessments. Each point represents the CHO predicted and the actual human visibility of the 81 configurations containing a defect.

Again, a strong correlation between the human and MO is visible and the area representing false negative decisions is still empty. It can be stated that the CHO is also valid for circular shaped defects.

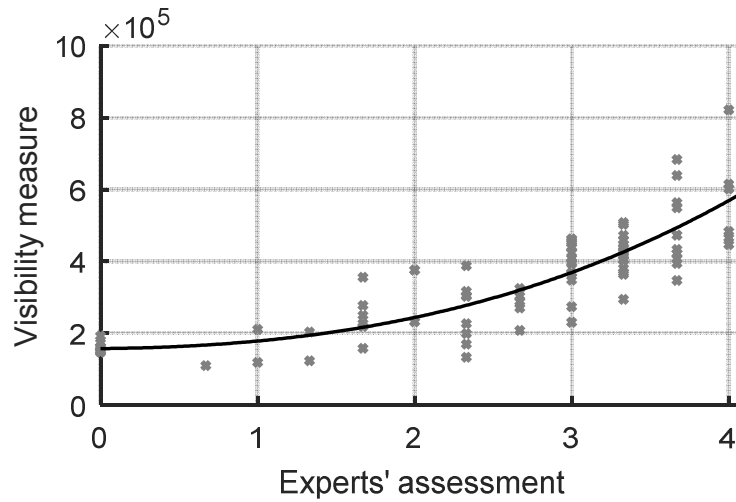


Figure 3.11 *Validation of CHO visibility measure by dataset using circular shaped defects including cubic fit*

3.5 Conclusion

It is the very first time known that the CHO as an established model of the human perception has been applied to the industrial environment and successfully validated. The results presented in this chapter prove that the CHO model is more appropriate than the existing models to predict human defect visibility in industrial applications. Thus the outcome of this research will hugely improve simulations carried out in NDE to get an objective measure of image quality in regard to human performance. Therefore, it is possible to improve radiographic tests in industry by not only modelling the setup and simulating the image, but also by evaluating the resulting simulated image automatically and more objectively compared to the existing visibility criteria. In addition, the gained information, such as the visibility comparison of circular and elongated flaws, will be very useful to further improve existing industrial standards as [45], [46].

A drawback is that the CHO results occur with a very high standard deviation (from 5 % up to 28 %) that will only decrease if the population size N_s is increased further. This can be explained by the significant noise, whereas less noisy images lead to more stable results. The noise model used has particular drawbacks such as an inability to generate correlated noise, and it is also unsuitable for small pixel sizes. Therefore, it is advisable to develop a new noise model. The next two chapters of this thesis are dedicated to that development.

Realistic film noise generation based on experimental noise spectra

As described in Chapter 2, there is a need to develop a new noise model to simulate realistic noise on the microscale. Therefore, a new film noise model is introduced, applied and validated in this chapter. It is experimentally based and relies on replicating the spatial frequency spectrum of real, original noise while randomising the phase spectrum. The method is able to generate unique samples of non-stationary noise with local spectral characteristics while ensuring pixel correlation throughout the image. Non-stationarity refers to the property that the generated noise shall have locally different spectra with varying grain coarseness throughout the image as seen in Figure 4.1. An important use of the model lies within industrial radiography to improve radiographic simulations by incorporating realistic film noise. However, the model is much more general and can be applied to any area where noise with local, space-varying spectral characteristics needs to be modelled. Therefore, the presented work has potential benefits in a broader context beyond this thesis, including areas such as photography and the movie industry.

The chapter starts in section 4.1 with an introduction including a review of film noise models that are published in the literature. This section is followed by an explanation of the theoretical background in part 4.2. Afterwards, the method is presented in section 4.3. The presentation includes a state-of-the-art method from

where the model is derived and its extension towards non-stationarity. This was developed in intense collaboration with Dr Nicolas Paul from EDF, who provided advice on the mathematical description of the state-of-the-art method based on filtering white Gaussian noise and its extension.

Furthermore, the method for processing the experimental data is presented followed by a detailed description of the new method in both its general and simplified versions, whereas the second version is specifically interesting in the NDE context. The following section 4.4 is dedicated to applying the new method and presenting the results including the validation of the method. The validation is performed visually as well as statistically. The chapter is then concluded in section 4.5.

The work presented in this chapter has been accepted as a research paper by IEEE Transactions on Image Processing [8] and the chapter follows the structure of the paper.

4.1 Introduction

The analogue photographic process stores an image on film by developing exposed silver halide particles to clusters of silver metal particles that form the image. The film-based image is characterised by a specific film noise pattern, usually visually perceived as a grainy texture. Film noise is a major influencer of image quality, and this visual noise is caused by spatial fluctuations of the image signal within uniformly exposed areas of the processed film. On the microscale, opaque clustering of exposed silver particles can be distinguished from transparent areas, when a microscopic analysis of a homogeneously exposed and developed film is performed. The Optical Density fluctuations in a uniformly

exposed film emulsion can be described by “granularity” measures [47]: these measures quantify objectively the optical noise due to film grain. In contrast to this, the term “graininess” specifies the subjective human perception of film noise due to granularity [48], [49]. The human eye is not able to resolve single clusters of exposed silver particles, called grains, which typically vary between $0.2\text{ }\mu\text{m}$ and $2\text{ }\mu\text{m}$ [50], [51]. These grains agglomerate in random patterns, which are however resolvable and appear as graininess [50].

Being an inherent feature of images stored on analogue films, grain noise can be undesirable and distracting. On the other hand, film noise is seen as an aesthetic feature of analogue photos often sadly missed in digital computer produced images or necessary for realistic image simulations. In the context of this thesis, realistic film noise needs to be generated in order to improve the simulation of film-based radiographs. Therefore, appropriate film noise generation can be vital to produce digital images visually not distinguishable from analogue film-based ones.

There have been many attempts through the literature to incorporate noise and these can broadly be classified into the following approaches: (1) repetition of stored noise, (2) generation of white Gaussian noise, (3) modelling of microscale noise and (4) using spectral approaches. The key methods (1) to (4) will now briefly be reviewed.

(1) The most straightforward way to incorporate noise is by adding a copy of stored film noise to the image. Although this deterministic approach is easy to implement, fast and may be reasonable for photos, it is particularly unfavourable to be applied to video sequences where each film frame would appear with exactly the same noise sample [52]. The noise is simply added in an uncorrelated manner to the signal (i.e. the true, noiseless) image, whereas in reality, grain

noise will generally be dependent on the underlying image and this should be accounted for in order to generate realistic noise.

(2) A second approach adds white Gaussian noise with a standard deviation defined by a one-parameter model based on the so-called Selwyn granularity [13], [47], [53]. That granularity measure assumes a constant relationship between the standard deviation of Gaussian distributed film noise and the square root of the scanning aperture [54] specifying the resolution. However, the assumed constant relationship does not apply to aperture sizes below $10\text{ }\mu\text{m}$ [49], [55]. In many applications, pixel sizes below $10\text{ }\mu\text{m}$ are often necessary. This leads to an overestimation of the noise intensity when the model is necessarily applied out of the range where Selwyn's formula is valuable and applicable. Similar noise approaches are applied in the post-processing of decompressed video sequences having removed the noise to increase compressibility beforehand [56], [57]. These white Gaussian noise models incorporate the spatial correlation between the noise and the image signal. However, these techniques do not respect internal spatial correlation between pixels of the noise. Internal correlation determines the grain size [58] and realistic modelling of it allows the generation of actual grain clustering on the microscale leading to graininess. This typical internal spatial correlation is missing. Furthermore, these procedures assume Gaussianity of the film noise, which is a restriction. The real-life complexity of true grain noise means that one parameter is unlikely to be sufficient to capture the properties in a general case. This second approach is implemented in industrial codes for simulating radiographs [42] and the main motivation of this chapter is to replace this model.

(3) Other approaches model the noise on the microscale as a grain distribution such as for example the Random Dot Models (RDM) [59]–[61]. These dot models

treat the grains as spatially randomly distributed disks absorbing the light. Newson *et al.* proposed a stochastic film grain model and rendering algorithm which is inspired by the physical photographic process and based on an inhomogeneous Boolean model respecting the local grey level [52], [62]. These microscale models are useful to generate an artistic grain effect, but the lack of consideration of experimental film noise fails to ensure the simulation of realistic film noise. As it is necessary to simulate each silver particle, these methods are computationally unsuitable for big or multiple noise images.

(4) Another grain noise model uses an analytical approach of the Noise Power Spectrum (NPS): white noise is generated and filtered in the frequency domain so that the spatial frequency spectrum of the noise matches with an analytical model for the NPS when transformed back to the spatial domain [63]. In order that the generated noise shows good agreement with empirical data, the analytical model needs to be adjusted by introducing specific characteristics of the noise: the diameter of single grains and of their clusters. So it is necessary to know these parameters from detailed dimension measurements of the film. Also, a noise sample using only one general NPS for the whole image is generated. Hence, the simulated grain pattern is without reference to the signal image that shall become noisy, which is potentially a disadvantage as the NPS should be dependent on the specific local exposure of the film. The combination of noise and image is achieved by a tone mapping adjusting only the contrast of the noise locally but not the NPS such that the grain size properties are constant over the whole image.

Given the key requirement to generate realistic, experimentally-consistent noise with minimal computational demands, this chapter introduces a new film noise model. While it is also based on the spatial spectrum of the noise, important

improvements of the presented approach compared to the existing literature are the use of real experimental data of homogeneously exposed films and the non-stationarity of the method to model noise with space-varying spectral characteristics. An alternative approach to the state-of-the-art method of filtering white noise is presented. This new approach allows the generation of unique phase spectra: by building up a randomised phase spectrum that meets specific conditions, it is possible to generate many unique instances of film noise conforming to the physical behaviour. Therefore, a repetition of identical noise patterns within the simulation result will never occur. Furthermore, the presented novel method allows the generation of non-stationary noise. Through this, the signal dependence of the noise is considered by respecting the relationship between local Optical Density and the spatial frequency spectrum of the noise because in the general case the noise is assumed to be statistically non-stationary. Additionally, the new model does not suffer from other disadvantages of the currently available noise synthesisers as it considers internal spatial correlation and it does not overgeneralise by only relying on limited numbers of extracted parameters. The cheapness in terms of computing capacity is another particular advantage of the new model. In its general form, it also avoids the assumption of Gaussianity currently relied upon by many film noise models.

Following some theoretical background in section 4.2, the new film noise generation method is presented in section 4.3. The method is exemplarily applied to and validated within the frame of industrial radiography, where X- or γ -rays are projected through a component onto a film to produce an image from which potential damage can be assessed. Representative results are provided and discussed in section 4.4 followed by the conclusion in section 4.5, outlining the impact of the method on image simulation in industrial radiography.

4.2 Theoretical background

This section is dedicated to highlight briefly the importance of the Film Noise Spectrum and its analogy in other disciplines, as well as recall the concept of Optical Density.

4.2.1 Noise Power Spectrum (NPS)

Clustering of grains as observable in film noise is caused by a correlation between pixels. This spatial correlation information can be extracted from a film noise image by the application of the 2D Fourier transform. The resulting spatial frequency spectrum, or Noise Magnitude Spectrum (NMS), describes the spatial periodicity of the image. In the case of film noise, the NMS contains the information about the graininess including the proportion of finer and bigger film grains. The accompanying phase spectrum describes the locations of these spectral components, and thereby the positions of the film grains. The squared form of the NMS is the 2D Noise Power Spectrum (NPS), also known as the Wiener Spectrum. The 2D NPS is the analogue to the 1D NPS used in electrical theory for noise representation in electrical signals [48], [49]. The spectrum contains information about the spatial frequencies of the noise and therefore stores data about spatial correlations or grain aggregations.

4.2.2 Optical Density

An exposed film consists of developed silver halide particles, which obstruct the visible light passing through the film by absorption, scattering, diffraction and reflection. When the film is examined on a negatoscope, higher exposed areas with more developed grains appear darker than less exposed areas. As already mentioned in Chapter 2 of this thesis, this film blackening can be quantified by

the concept of “visual diffuse Optical Density” (OD, see ISO 5, parts 1–3). The OD ranges usually between $OD = 0$ for totally transparent to $OD = 6$ for almost totally opaque. The greyscale values (GV) in the calibrated digital film images are similarly defined: $GV = 0$ is represented by white and $GV = 60000$ by almost black. Within radiography, the OD represents the measurement signal giving information about the investigated state of the object during exposure. The OD is affected by noise, specifically X-ray radiation mottle and grain noise.

4.3 Method

The idea of the noise generation method introduced in this chapter is to use the NPS to model non-stationary noise realistically using experimental data. In summary, this can be done by deriving the NPS experimentally, randomising the phase spectrum and applying the inverse transform from the spatial frequency domain back to the initial image domain. A more general approach is first described, then simplified for the specific case of film noise generation within industrial radiography.

In the following paragraphs, the state-of-the-art method in generating stationary noise with specific, homogenous spectral properties is presented. A key contribution of this thesis is that the approach will be generalised to the non-stationary case, where the NPS varies locally as the underlying image signal changes enabling the method to be effectively applied for noise generation problems even beyond the field of industrial radiography. Afterwards, the new method and its implementation will be presented.

4.3.1 State-of-the-art

In the introduction of this chapter, a noise generation method was briefly introduced that generates noise by filtering white noise with a specific NPS [63]. That filtering approach is the state-of-the-art method for generating stationary noise with target inter-correlation and shall be described in more detail in the following paragraphs. The method can be summarised as:

1. White Gaussian noise is generated,
2. the noise is filtered in order to control the noise correlation,
3. the contrast is adjusted so that the generated noise looks like the desired noise.

The state-of-the-art stationary case is first considered, which can be used when the noise power spectral density and probability density functions are constant over the entire image. The method to generate noise, having a given inter-correlation, consists initially of generating Gaussian noise which has values which are normally distributed with a constant (white) power spectral density. The generated white Gaussian noise is afterwards filtered so that the result after filtering has an inter-correlation represented by a specific target autocorrelation function $\gamma(x, y)$ where the arguments x and y describe the Cartesian coordinates in the spatial domain. The autocorrelation function γ describes the covariance between two pixels $\mathbf{x}_1(x_1, y_1)$ and $\mathbf{x}_2(x_2, y_2)$ which depends only on their difference $\mathbf{x}_1 - \mathbf{x}_2$. The Wiener–Khinchin theorem states that the power spectral density of a wide sense stationary random process (which is supposed for the noise regarded here) is equal to the Fourier transform of the autocorrelation function of the random process [64]. This means that the NPS is the Fourier transform of the autocorrelation function of the noise [64]

$$NPS(\nu, \xi) = \mathcal{F}_{2D}\{\gamma(x, y)\} \quad (4.1)$$

with $\mathcal{F}_{2D}\{\cdot\}$ as the 2D Fourier transform and the arguments ν and ξ as the coordinates in the Fourier domain. The filtering is achieved by convolving the white Gaussian noise u_{wg} with a filter h with frequency response $H = \mathcal{F}_{2D}\{h\} = \sqrt{NPS}$, leading to noise v

$$v = h * u_{wg} = \mathcal{F}_{2D}^{-1}\{H \cdot U\} = \mathcal{F}_{2D}^{-1}\{\sqrt{NPS} \cdot U\} \quad (4.2)$$

where $*$ describes the convolution and U is the Fourier transform of u_{wg} . The filter operation can be described as perturbing the amplitude spectrum of the initially white Gaussian noise. The resulting noise v has the target power spectrum and therefore the required inter-correlation given by H , because U is the Fourier transform of white noise with a completely flat power spectral density and has no influence on the spectrum of v . Furthermore, v has a new phase spectrum because of the multiplication with the random phase of U . This can be interpreted as imposing on v the new random phase of u_{wg} . That interpretation is of importance when describing the new method in section 4.3.4.

The resulting noise has the target frequency spectrum and therefore the desired correlation. In addition, the noise Probability Density Function (PDF) is Gaussian because the filtering of white Gaussian noise (u_{wg}) remains Gaussian. The PDF describes the contrast of the noise. In the general case, the final target noise may have a different PDF which might be non-Gaussian. Therefore, it is generally not enough to only ensure the correlation matches. Also, the PDF and hence the contrast must be adjusted for correct texture reproduction. Considering the Gaussian case specifically, the target Cumulative Distribution Function (CDF) of the Gaussian distribution $G(w)$ is introduced as

$$G(w) = \int_{-\infty}^w g(z) dz \quad (4.3)$$

with $g(z)$ as the Gaussian PDF. The final contrast adapted target noise w can then be calculated by

$$w = F^{-1}(G(v)) \quad (4.4)$$

with $F(w)$ as the known target CDF. The resulting target noise has then also the desired contrast in addition to the desired inter-correlation. It should be highlighted that the contrast correction does change slightly the correlation. However, these changes are small if the target distribution is close to a Gaussian distribution [65].

4.3.2 Extension of the state-of-the-art method towards non-stationarity

So far, the presented state-of-the-art method allows the generation of stationary noise. The difficulty in generating non-stationary noise is to respect space-varying spectral characteristics. E.g. it was expected by the author that the exposure amount and therefore the mean signal (OD) would have an influence on the coarseness of the noise pattern. This was the initial motivation for extending the state-of-the-art noise model towards non-stationarity. At a later stage in this chapter, it will be shown that this hypothesis could not be verified for industrial radiography. To establish a localised stationary or “semi non-stationary” approach, it is possible to segment the image into areas of similar signal values and to generate stationary noise independently for these areas. But this approach neglects inter-correlation between the different noise segments and leads to undesired borderline effects, which can, however, be reduced to an extent by smoothing [66]. The stationary state-of-the-art method is now extended for non-

stationary noise with local statistics and the inter-correlation between the generated noise samples of neighbouring sections is taken into account.

Let $\mathbf{x} = (x, y)$ be the pixel position and $d(\mathbf{x})$ the signal at position $\mathbf{x}$ of the image to which noise should be added. It is supposed that the signal $d(\mathbf{x})$ has an impact on the local noise properties such as NPS and PDF. Therefore, the local NPS is defined as $NPS_{\mathbf{x}}$ and the local target CDF as $F_{\mathbf{x}}$.

The white noise filtering approach was given by (4.2) for the stationary case. In the spatial domain, this noise generation can be seen as a simple spatial filter

$$v = h * u_{wg}. \quad (4.5)$$

The stationary noise generation is a spatial filtering of white noise. Now, in order to generate non-stationary noise with local spectrum $\sqrt{NPS_{\mathbf{x}}}$ it is proposed to spatially adapt the filtering coefficients to the target NPS

$$v(\mathbf{x}) = h_{\mathbf{x}} * u_{wg} \quad (4.6)$$

with

$$h_{\mathbf{x}} = \mathcal{F}_{2D}^{-1} \{ \sqrt{NPS_{\mathbf{x}}} \}. \quad (4.7)$$

As in the stationary case, this adaptive filtering operation can be performed in the frequency domain

$$v(\mathbf{x}) = \mathcal{F}_{2D}^{-1} \left\{ \sqrt{NPS_{\mathbf{x}}} \cdot \mathcal{F}_{2D} \{ u_{wg} \} \right\} (\mathbf{x}) \quad (4.8)$$

and, as mentioned in section 4.3.1, the noise Fourier transform operation $\mathcal{F}_{2D} \{ u_{wg} \}$ can be replaced by a phase randomisation of $\sqrt{NPS_{\mathbf{x}}}$.

A final contrast adaptation is also needed. If $G_{\mathbf{x}}$ is the (Gaussian) cumulative distribution function of $v(\mathbf{x})$ the contrast local adaptation is given by

$$w(\mathbf{x}) = F_{\mathbf{x}}^{-1}(G_{\mathbf{x}}(v(\mathbf{x}))) \quad (4.9)$$

and the resulting noise is non-stationary with local statistical properties. An example result of that method is shown in Figure 4.1.

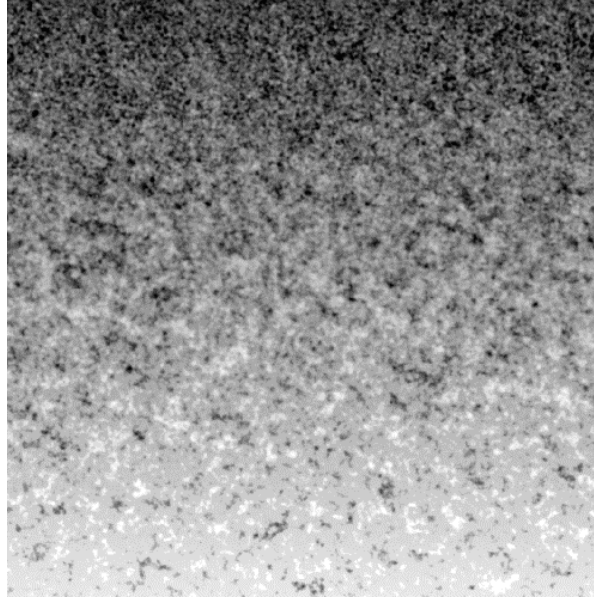


Figure 4.1 *Example result of non-stationary noise with locally varying spectral properties*

4.3.3 Generation of the experimental database

Based on the above derivation, it is necessary to provide NPS data for all signal values at any position $\mathbf{x}$. This is rarely possible in practice, because only NPS data for a limited, discrete number of signals, can be measured. A method to simulate NPS data for any signal case is also presented in this section.

The approach to establish a database of NPS information is based on experimental data of noise that was gained under various signal conditions under

which the signal is expected to have a direct impact on the noise statistics. Because the method is developed for the 2D space, 2D images of noise represent the experimental basis. These experimental images should be homogenous in terms of the mean signal to ensure that the noise statistics are stationary and well defined for each investigated signal case. The statistics of the 2D noise for a specific mean signal are assumed to be determinable from a single noise realisation, a property known as ergodicity. Furthermore, the statistics of noise are assumed to be constant over an area of homogenous mean signal. Hence the noise is statistically stationary if the signal is homogenous. [64]

The first step consists of subtracting the mean value (the signal) from the homogenous, experimental image to get an image of the pure noise fluctuations N . To derive the spectral properties of the noise in this specific signal case, the NPS of the noise is given by

$$NPS = \lim_{X,Y \rightarrow \infty} \left\langle \frac{|\mathcal{F}_{2D}(N)|^2}{(X \cdot Y)^2} \right\rangle \quad (4.10)$$

where $\mathcal{F}_{2D}$ represents the Fourier transform in 2D, X, Y are the dimensions of the noise image N in both spatial directions and $\langle \rangle$ denotes the ensemble average.

Because ergodicity is assumed, the noise properties relating to a specific mean signal can be deduced from only a single noise sample of that specific signal value. For the practical implementation, the noise image is cut into sub-images of equal dimension. The size of the sub-images influences the resolution of the generated NPS and should be chosen appropriately for the investigated case. Averaging the NPS over n_{si} sub-images leads to a better estimation for the NPS, known as the Welch's method [67], [68]. The image is split into as many non-overlapping sub-images as possible.

A 2D Fast Fourier Transform (FFT) of the sub noise images is performed to calculate the 2D NPS

$$NPS = \frac{1}{n_{si}} \sum_{i=1}^{n_{si}} \frac{|\text{FFT}(N_i)|^2}{(p_x \cdot p_y)^2} \quad (4.11)$$

where NPS is the averaged and normalised NPS of the noise image in 2D, n_{si} is the number of sub-images, N_i is the i -th sub-image and p_x, p_y is the dimension in number of pixels in the x (respectively y) direction of the sub-image.

The amplitude spectrum specifies which spatial frequencies are present in the original noise image and to what extent; this spectrum can be interpreted as information about the fineness of the noise. Therefore, the magnitude of the NPS for each signal case is stored in a database together with the information of the signal that is related to the specific noise sample. Furthermore, the standard deviation for each signal case is stored as well. The phase spectrum, however, provides different information about the spatial location and therefore the location of the noise textural components; this is therefore not needed because an artificial phase spectrum will be created later. A new random phase spectrum ensures that a unique noise realisation will be generated by perturbing the local appearance of the noise features (grain locations).

In the case where noise is directionally independent, the 2D NPS spectrum can be transformed into a 1D representation, exploiting the circular symmetry of the 2D NPS spectrum. Considering the 2D NPS in polar coordinates (r, θ) in radial and circumferential directions respectively, the axial symmetry indicates that the function should be independent of θ and hence purely a function of r . A 1D function representation of the 2D NPS can be achieved by averaging around the circumferential direction. By convention, the lowest spatial frequencies are

located around the origin and higher spatial frequencies are located near the edges of the 2D NPS. The resulting 1D NPS can then be stored more efficiently.

In addition to the spectral information, the histogram describing the distribution of the fluctuations of each investigated noise sample needs to be calculated and stored in the database. The histogram is necessary to adapt the contrast of simulated noise correctly at a later stage.

So far, it was described how the database of experimental data can be established. The procedure is summarised in Figure 4.2. This procedure needs to be repeated for each film type.

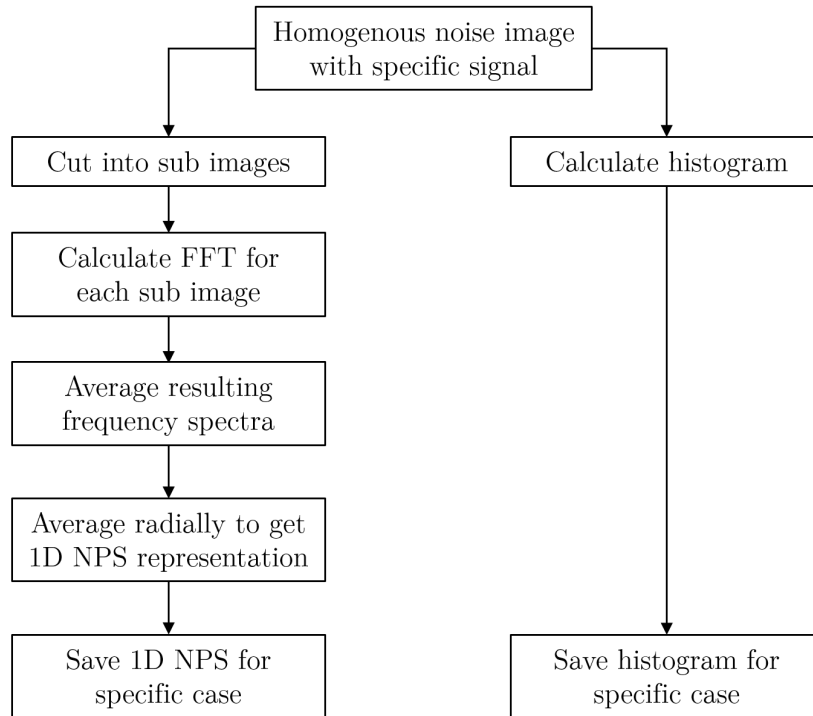


Figure 4.2 *Flowchart of the approach to build up an experimental database; the process is repeated for any available homogenous noise image of the database*

4.3.4 Generation of the noisy image

Having deduced the spectral and probability density information from experimental data, it is necessary to process the “input image”, which refers to the image to which noise should be applied. In summary, noise is generated selecting the 2D NPS matching the local signal value of the input image, generating a random phase and transforming back from the Fourier in the spatial domain to locally generate noise with the required correlation, and in a last step, adjusting the contrast such that it looks like the desired noise. This approach is only possible selecting one specific NPS relating to one specific signal value.

Generally, in the non-trivial case, the input image is not homogenous but has varying intensity. Consequently, noise needs to be generated respecting the local signal. Because the method needs to simulate non-stationary noise, the frequency information must be space dependent.

The algorithm can be summarised as follows:

1. Splitting the input image up into non-overlapping segments,
2. allocating to each segment a spatial frequency spectrum
 - a. defined by one specific NPS available from the database
 - b. or if not available, interpolated between available data to generate the required NPS,
3. generating a random phase matrix with the dimension of the input image,
4. for each segment, performing an inverse Fourier transform to generate a new noise sample with the dimension of the input image,

5. modifying the contrast of the generated noise so that it looks as the desired noise,
6. assembling the final noise image by
 - a. masking the generated noise images so that only the noise within the region of the segment remains, all other pixel values are set to zero
 - b. putting together all the masked noise samples to the final noise image
7. the final noisy image (input signal image with noise) is produced by adding the generated noise image to the input image.

The input image is segmented into discrete areas of comparable signal values to which the noise generating approach is applied separately. The segmentation is performed by a histogram-based approach allocating each grey-level of the input image to a specific segment. A segment, therefore, contains all the pixels within the specified grey-level (signal) range of the input image. The noise generation is then performed for each segment separately. The approximation of the localised noise generation is better with a higher number of segments. For example, the image in Figure 4.1 was generated by segmenting the input image in 20 areas. A straightforward approach is to segment the input image into areas of comparable mean signals, whereas the mean signals are chosen to be uniformly distributed within the overall signal range of the input image. To each area, noise associated with the specific signal corresponding to the mean of that area can be added.

For each segment, a suitable NPS needs to be computed and assigned corresponding to the mean signal. As the database contains only NPS information relating to discrete signal values, it is unlikely that the specific NPS

is available. To generate a reasonable NPS, the selected approach is to perform a linear interpolation to a specific NPS between the nearest NPS datasets above (NPS_1) and below (NPS_0) the mean signal value, by a simple weighting approach

$$NPS_\delta \equiv (1 - \delta)NPS_0 + \delta NPS_1 \quad (4.12)$$

with the weight $\delta \in [0,1]$.

Afterwards, in the case of isotropic, omnidirectional noise, the interpolated 1D NPS can be expanded to a full 2D NPS by rotating the 1D function through 360 degrees around its origin. In the case of non-omnidirectional NPS where the full 2D functions have been stored, these can clearly be used directly. The resulting 2D NPS is resized by stretching the spectrum to the noise image target dimension using a bicubic interpolation. Alternatively, that stretching can also be performed by interpolation on the 1D NPS before rotating through 360 degrees. This interpolation procedure is repeated for all defined input image segments. In an analogous manner, the histograms matching the mean signal of all segmentations are also interpolated.

In the extreme case, the noise is generated separately for each pixel of the input image. In this case, the number of segments would be equal to the number of different signal values in the input image. Then, the noise for a specific pixel was generated using an NPS which matches the signal value of exactly that pixel. However, because of the computational cost which would arise from doing this with high-resolution images (an inverse FFT of the full size of the input image needs to be performed for each segment), it is advisable to generate noise matching only the mean signal of areas of the input image.

In order to create a new noise sample containing the spatial frequencies defined by the spectrum but not just creating a copy of the original experimental noise image, a new phase spectrum needs to be generated. It is assumed that the investigated noise has a random phase texture. This kind of texture is characterised by a random nature of its phase spectrum [69]. The main information about the noise appearance is stored in the amplitude of the frequency spectrum. Generating random phase textures with a given spatial frequency spectrum is possible by randomising the phase spectrum and the application of the inverse Fourier transform [70]. It can be noted that the state-of-the-art method filters white Gaussian noise, which is also similar to randomising the phase [71].

The new phase spectrum matrix with the target dimensions is built up by assigning uniformly distributed random values lying within the phase range of $[-\pi, \pi]$ to each element of the phase matrix. It is necessary to build the matrix in a way that Hermitian symmetry is assured. A complex square matrix is Hermitian if the matrix is equal to the matrix's own conjugate transpose. A single artificial phase matrix is generated for all noise samples to be generated across the image, to ensure intercorrelation of the noise samples for different segments. This minimises the possibility of visible borderlines occurring within the noise on segmentation borders. This approach is similar to the generalised version of the state-of-the-art method in (4.6), where only one and the same Gaussian noise u_{wg} is used.

Afterwards, the Inverse FFT (IFFT) is calculated combining the amplitude as well as the artificially created phase spectrum. Here the Hermitian symmetry of the generated phase matrix is crucial to guarantee real numbers after applying

the IFFT. The resulting noise image has approximately a Gaussian distribution [69] of its grey values and needs contrast correction.

It is necessary to correct the probability density of the generated noise so that it becomes similar to the target noise, i.e. the pixel intensity distribution of the artificial noise needs to be similar to the experimental noise (or to an interpolated case between available experimental cases). In contrast to the state-of-the-art method where the target CDF of the noise is needed, the histogram of the target noise is used. This was achieved by histogram matching using the histogram equalisation function “histeq” provided by MATLAB [72]. The function computes a greyscale transformation function V , which minimises the difference between the cumulative histogram (cumulative distribution function, CDF) c_0 of the image to be processed and the cumulative target histogram c_1 for all pixel intensities i_P

$$\min |c_1(V(i_P)) - c_0(i_P)|. \quad (4.13)$$

The result of this is that the created noise sample has the same probability density function as the initial noise after application of the greyscale transformation function V .

The assumptions have been made that the investigated noise has a random phase texture, is ergodic and a wide sense statistically random process, and is also directionally independent. The resulting images are new noise samples visually comparable to the original noise with the same signal. Because the phase spectrum is kept unchanged for each generated noise sample, no borderline becomes visible when merging the noise segments. The merging of the final noise image is achieved by assembling the segments of separately generated noise areas. Every pixel in the input image was allocated to a segment, and the noise values

were then generated within each segment independently. The noise value in the final image for each pixel was just taken from the segment containing that pixel. In practice, the generated noise images are masked so that only the noise within the region of the segment remains and all other pixel values are set to zero. Then, all the masked noise samples are summed to form the final noise image.

In a last step, the generated noise image w is added to the input image I_{input} to receive the noisy input image $\tilde{I}$

$$\tilde{I} = I_{input} + w. \quad (4.14)$$

The method for generating a non-stationary noise image is also summarised in Figure 4.3 and an application result is presented in Figure 4.1.

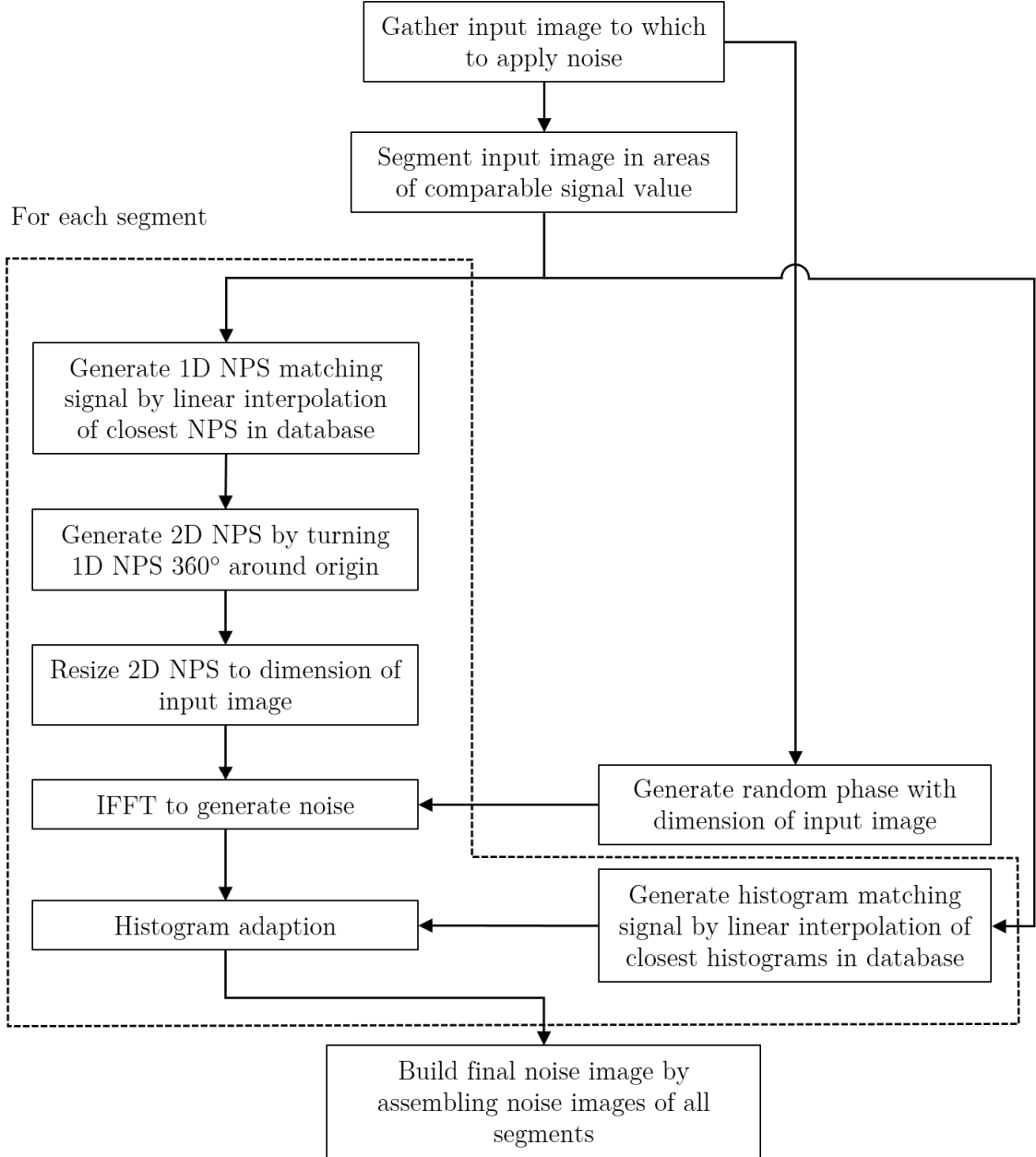


Figure 4.3 Complete process for generation of non-stationary noise

4.3.5 Simplified method for simulating statistically non-stationary noise

In some scenarios (for example with film noise in industrial radiography), it may be possible to simplify the general method described above. These simplifications can reduce the computational cost when generating noise by the presented model

and they would reduce the experimental effort necessary to deliver the input data for the noise model. Two assumptions will be presented in this section to be incorporated in the general non-stationary noise model: that the NPS for different signal cases is collinear and scalable by the standard deviation, and that the grey-levels of the noise are Gaussian distributed.

The Wiener-Khinchin theorem leads to an important feature of the NPS: the volume under the 2D NPS is equal to the variance of the measured signal variations [64]

$$\sigma^2 = \iint NPS \, du \, dv \quad (4.15)$$

where σ denotes the standard deviation of the noise image and u, v are the spatial frequencies in both Cartesian directions. The values in the autocorrelation function, normalised by mean and variance, are referred to as the autocorrelation coefficients. Assuming that the autocorrelation coefficients of noise images with different average signals are identical, it is possible to scale the underlying NPS by the formula

$$NPS_{target} \equiv \left(\frac{\sigma_{target}}{\sigma_{basis}} \right)^2 NPS_{basis} \quad (4.16)$$

where NPS_{basis} and σ_{basis} are respectively the NPS and the standard deviation of the image used as the scaling basis, σ_{target} is the known standard deviation of a target noise image with mean signal to which the NPS shall be scaled to and NPS_{target} is the NPS of that target noise image. Therefore, it is possible to generate noise for the whole input image by just considering a single NPS for any signal value and scaling appropriately. The signal related NPS data is derived from a specific experimental image with a clearly defined, homogenous signal. Practically, noise images are only available for a limited number of signal values

not covering the whole possible signal range because of the challenges of acquiring experimental data. The described approach to scale the NPS to a specific signal value solves the problem of having available only a limited number of NPS data.

Furthermore, it is assumed that the noise distribution is Gaussian, hence the histogram shows a normal distribution [9]. Given that original noise and simulated noise are both characterised by a Gaussian distribution, the simulated noise does not need any further contrast adaptations via histogram modifications. For this reason, only the standard deviation of the generated noise image after performing the IFFT needs to be corrected. The target standard deviation is calculated by linear interpolation using the standard deviation data stored for specific signals in the NPS database. To respect the non-stationary dependency between noise and signal, the standard deviation is adjusted pixel-wise.

4.4 Application results and discussion

In this section, the method is demonstrated on the example of noise represented by fluctuations of OD on radiographic or photographic film. Specifically, the application and validation of the noise generation method are described for the case of film noise simulation in industrial radiography. Realistic image simulation is of high interest for industrial radiography in NDE.

As already outlined in Chapter 2 of this thesis and recalled here, radiography is an NDE method based on shadow greyscale images formed by high energy photons passing through and becoming attenuated partially by the object to be imaged. Digital detectors or analogue film can be used to capture the image. Despite the rise of digital approaches, film radiography continues to be widely

used, particularly in more conservative areas such as the nuclear industry which necessarily relies upon well-established and very reliable testing techniques. In the industrial context, the harmfulness to biological tissue is secondary because of non-biological objects. Furthermore, in industry, film-based radiography can often be quicker and cheaper than digital methods when undertaking small numbers of exposures on various locations because of the reduced calibration effort.

In film-based radiography the resulting shadow image is stored on the film by localised blackening due to the exposure and development of silver halide crystallites by arriving and interacting X- or γ -rays. The crystallites become opaque to visible light as a result of their exposure and the opaqueness is amplified by the development process. The resulting shadow image contains image information about the subsurface of the object and enables the visual detection of potential defects within the object present at the time of exposure. Radiographs of technical components consist of gradients of OD due to local variability of penetrated wall thickness and/or object material along the radiation paths. Therefore, spatial variability of the OD and hence the signal in the input image is almost always present.

Because of the expense of performing these tests, computational simulations are a vital tool in order to produce realistic images and hence establish the best testing approach [6]. These simulated images are afterwards assessed for the purpose of indirect, computer-based test setup improvements or testing procedure qualification [7]. For that reason, the simulated X-ray images need to be as realistic as possible, which includes an appropriate modelling of film noise too. Film noise in the form of graininess is a major obstacle in reliably detecting defects [73] in real X-ray images and must be simulated too.

In section 4.4.1, the characteristics of film noise are presented, allowing the assumptions necessary for the application of the simplified method presented in section 4.3.5 to be made. Afterwards, section 4.4.2 describes how noise samples were obtained, followed by validation studies. Comparing original and artificial film noise by visual inspection is the standard validation method of film noise synthesisers because of a lack of objective measures to quantify the closeness between generated and real film noise [74]. Nevertheless, an image feature extraction method established in the area of texture analysis basing on co-occurrence matrices [75] was applied to compare simulated and real noise quantitatively. In that sense, the resulting noise images were visually and quantitatively compared to the original data for validation in section 4.4.3 respectively in section 4.4.4.

4.4.1 Film noise characteristics

The random process of film noise is assumed to be ergodic and the statistics of film noise are assumed to be constant over a homogeneously exposed and developed area. Hence film noise is statistically stationary if the signal is homogenous. Therefore, the noise properties relating to specific exposure and development conditions can be deduced from only a single film sample exposed and developed under these conditions [64].

Furthermore, exposure by photons (such as X-rays or γ -rays) is a quantum-limited process and it is expected that the radiation follows quantum statistics. Hence, the resulting noise has Poisson noise characteristics [12]. The characteristic of the Poisson distribution is that its variance is equal to the expected number of quanta. The so-called Nutting formula [60], [64] describes how the OD is proportional to the number of exposed particles in the film emulsion

$$OD = 0.434 \frac{n_A \bar{a}}{A} \quad (4.17)$$

with n_A as the number of exposed particles within the film area A and $\bar{a}$ is the mean projection area of the particles. It can be assumed that the number of exposed particles is proportional to the number of exposing photons. Therefore, it is concluded that the OD is proportional to the exposure dose and hence proportional to the squared standard deviation of OD fluctuations because of their Poisson distributed nature. The proportionality of granularity σ to the square root of the OD is known as the Siedentopf relationship [64].

The Central Limit Theorem in probability theory states that the sum of an increasing number ($n \rightarrow \infty$) of independent random variables tends towards a normal distribution. The photons exposing the particles are assumed to be independent of each other and during exposure, a very large number of photons leads to a very large number of exposed particles in the film emulsion. These considerations allow the assumption that the film noise distribution is approximately Gaussian. Experimental work using NDT films [9] has verified that the distribution of the original noise images is practically Gaussian distributed. This work is more detailed in Chapter 5 of this thesis. Supposing the Siedentopf relationship, the target standard deviation is calculated by linear interpolation using the standard deviation data stored for specific mean OD signals in the NPS database.

Experimental work, presented in the paper [9] and also described in Chapter 5 of this thesis, has shown that the autocorrelation coefficients of film noise images with different mean OD (the signal) but exposed under the same conditions are almost identical for the case of film noise. This indicates that the NPS for different OD are collinear, and hence implies that the same NPS can be used for

generating noise of all signal values when all other experimental conditions such as exposure energy remain constant.

4.4.2 Experimental description

For the example of radiographic or photographic film noise, light microscopic images of film samples (including fog and film base) form the experimental basis of the presented method. The film samples are exposed and developed homogeneously but gathered under different exposure conditions such as time, energy or intensity to gain experimental data for various mean signals.

First, appropriate input image data was gained. An experimental setup consisting primarily of a digital camera and an objective lens was used [9] to investigate AGFA STRUCTURIX films of three different film system classes C1, C3 and C5 in accordance to [13]. That experimental setup is further detailed in Chapter 5 of this thesis. The films were homogeneously developed and exposed under various conditions such as different exposure times, energies and filter screens. The film system class defines standardised film quality properties including ISO speed and a general noise behaviour in terms of a standardised measurement of the Selwyn granularity. Film samples with Optical Densities (OD) in a range between around 0.3 and 4.9, which is the usual OD range in industrial radiography, were investigated. The grey value images were calibrated to $GV = 10000 \cdot OD$. These data provide a vast collection of input images to validate the noise generation method described above. Further description of the experimental setup can be found in [9] and in Chapter 5 of this thesis.

4.4.3 Visual validation

The visual perception of noise to a human observer depends principally on the spatial power spectrum and the signal-dependence of the noise power [76], both of

which are incorporated in the presented model. The visual comparison was conducted by comparing the overall and in detail appearance of the noise on a high quality medical display system (EIZO RadiForce RX340). The visual comparison was performed by untrained assessors but who are familiar with industrial radiology. A first example is shown in Figure 4.4. This is a case of a C3 film, exposed with an Iridium-192 source with an activity of 11 Ci for 120 min from a distance of 2 m, and using two 0.2 mm lead screens placed on either side of the film. An image with varying OD, generated by a tungsten wire of 0.8 mm diameter as the object, is displayed in the top left part of the figure. A synthetic, ‘clean’ version of this is then generated by averaging horizontally to produce the image in the top centre. Finally, on the top right artificially generated noise using the simplified method presented in this chapter is incorporated into the clean image to test the performance. Visually the perceptions of the noise are indistinguishable. This is reinforced with the zoomed images on the bottom row of the figure.

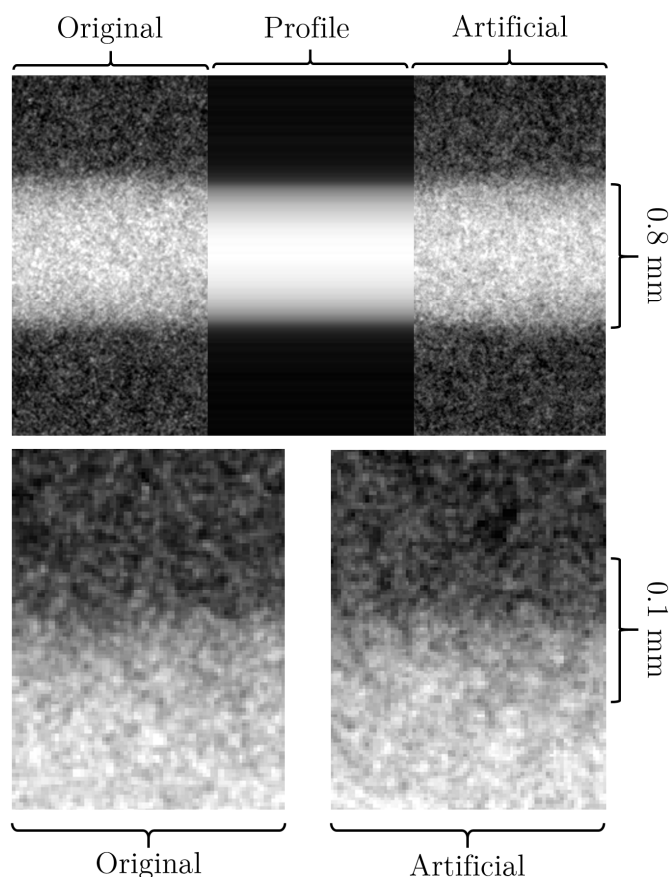


Figure 4.4 *Comparison of original noise (top left), profile (top centre) and artificial noise (top right) with 8 times zoomed details of original noise (bottom left) and artificial noise (bottom right)*

Additionally, the influence of the noise on the visibility of indications within the radiograph was investigated. Noise is known to be a major influencer on the image quality, degrading the detectability of small indications such as defects within industrial radiographs. The established method for measuring image quality is to investigate the visibility of Image Quality Indicators (IQI) on the radiograph attached to the object during exposure. IQIs consist of features such as holes or wires of decreasing size, with the intention that the feature at the limit of visibility will provide a quantitative measure of visibility. Figure 4.5 shows in part a) an original image of a duplex wire IQI pair D11 (ISO 19232-5) on the same film as described above. The pixel size is $6.662\text{ }\mu\text{m}$. The IQI is nearly

not visible and it is impossible to distinguish between the two separate wires because of the noise. Part b) of the figure shows the profile of the wires when the noise in image part a) is removed by horizontally averaging. Here the two wires are visible separately. In part c), noise generated by the (simplified) method presented in this work is added. The IQI becomes similarly invisible as in the original image. Figure part a) and c) look visually alike. When comparing with the noise generated using white Gaussian noise as currently performed in simulation [42], the resulting image looks much different as shown in part d).

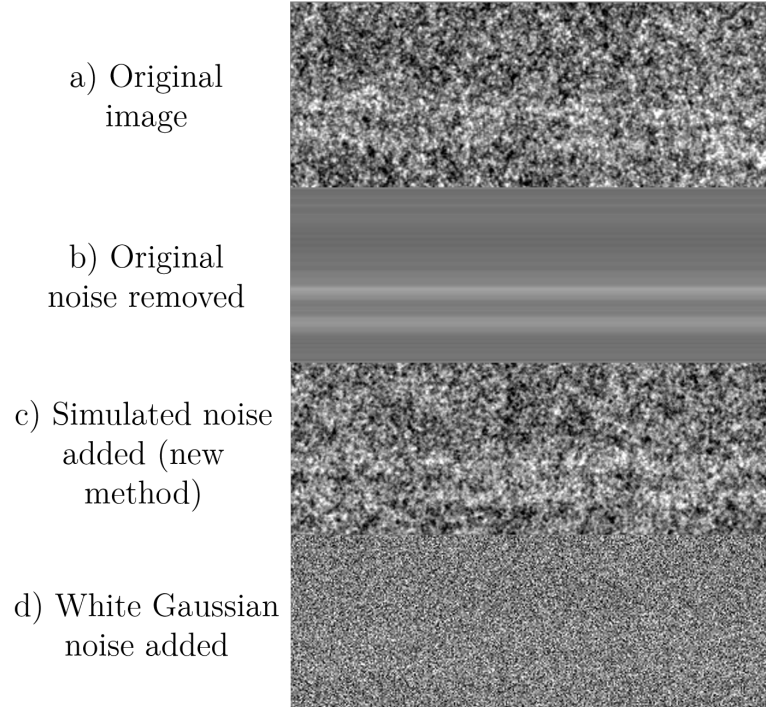


Figure 4.5 *Original image of duplex wire IQI pair D11 (a), IQI wire pair profile extracted (b), noise generated by the new method added to the profile (c), white Gaussian noise added to the profile (d); IQI wire pair diameter: 0.08 mm each*

It was also investigated if the simulated noise is valid also when using another digitisation method than the optical setup. A film can be digitised alternatively by a laser scanner. The same film as above was digitised by the scanner model “Array 2905 HD Laser Film Digitizer” with 50 μm pixel size. A pixel size of

50 μm is currently the state-of-the-art in laser scanner technology. Four wire pairs of the IQI according to ISO 19232-5 of different diameters are shown in part a) of Figure 4.6, from well visible (IQI wire pair D10 on the very left) to almost invisible (IQI wire pair D13 on the very right). Again, the noise was removed by this time vertically averaging the original image to extract the profile of the IQI lines. It can be stated that all the four IQIs are well visible in this profile image in part b), but only D10 is resolved clearly. Therefore, the basic spatial resolution of this image is determined to 0.08 mm by D11 according to ISO 19232-5. In contrast, in Figure 4.5 D11 is clearly resolved, which is the result of the high resolution digitisation by the camera system in comparison to the laser scanner. The presented simplified noise generation method is then applied to this noise reduced image. The result is presented in part c) of Figure 4.6 where the IQI on the very right is again almost invisible. It can be stated again that the noise generated by the new method has a similar effect on the visibility of small indications as the original noise and the overall appearance of the image with artificial noise is indistinguishable from the original image. These comparisons prove visually the effectiveness of the noise generation method based on phase randomisation.

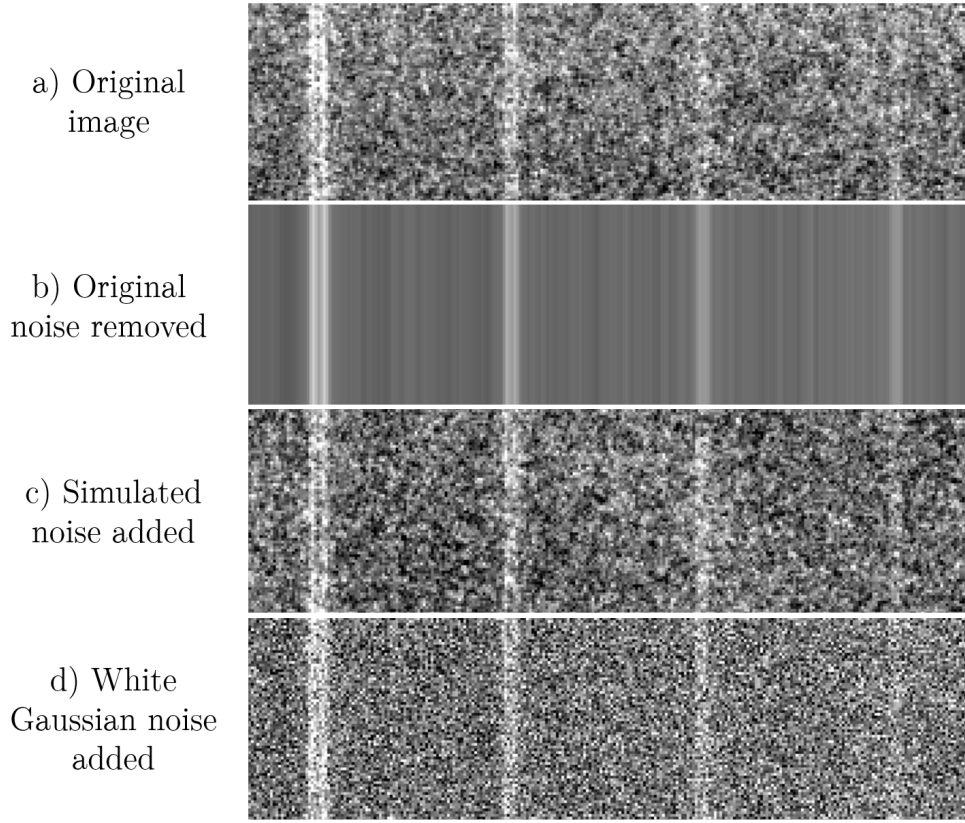


Figure 4.6 *Original image of duplex wire IQI D10 to D13 taken by a laser scanner (a), IQI profile extracted (b), noise generated by the new method added to the profile (c), white Gaussian noise added to the profile (d)*

4.4.4 Statistical validation

While the visual validation results demonstrate the realism of the simulated noise, it is important to perform some form of quantitative measure in order to confirm that the behaviour matches. Analysis of the spectrum would commonly be a good assessment method, however, this is unsuitable here since the spectrum itself has been used to generate the noise. Instead a statistical method to compare simulated and real data was applied. In the field of texture analysis, the image feature extraction method based on Grey Level Co-occurrence Matrices (GLCM) is well established [77]. It was suggested by Dr Nicolas Paul from EDF to use this method in order to validate the noise model statistically. The co-occurrence

matrix of an image is a second-order statistical measure considering the spatial relationship and grey-level combination of two pixels. It is assumed that the human visual system can only distinguish between original and simulated noise if they differ in the first or second-order probability distributions [78], [79]. Across the whole image, the matrix describes the probability of pixel value combinations that occur at two positions in a predefined distance. The spatial relationship between these two pixels of interest is defined by an offset vector.

The GLCM for a specific offset is calculated by

$$GLCM_{\Delta x, \Delta y}(i, j) = \sum_{x, y} \begin{cases} 1, & \text{if } B(x, y) = i \text{ and } B(x + \Delta x, y + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \quad (4.18)$$

with $B(x, y)$ as the image pixel value at position (x, y) and $(\Delta x, \Delta y)$ define the offset between the two investigated pixels. Figure 4.7 shows an example of how the GLCM is assembled for a $4 \cdot 4$ matrix of grey levels between 1 and 4 with an offset of $\Delta x = 1$ and $\Delta y = 0$.

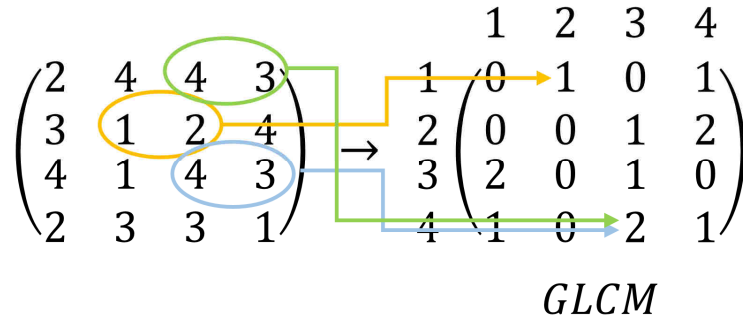


Figure 4.7 *Assembling the GLCM*

Image features can be extracted by calculating statistical measures from the GLMC, such as contrast, correlation, energy or homogeneity. These statistical measures have been defined in [75] and they are interrelated and have

redundancies [80]. This chapter focuses on comparing the statistical property of contrast. The contrast feature C^{GLCM} is defined as

$$C_{\Delta x, \Delta y}^{GLCM} = \sum_{i,j} |i - j|^2 GLCM_{\Delta x, \Delta y}(i, j) \quad (4.19)$$

and measures the intensity contrast over the whole image between two pixels in a spatial relationship described by the offset vector $(\Delta x, \Delta y)$.

The investigated homogenous noise sample was exposed on a system class C1 film with a 220 kV X-ray tube using an 8 mm Cu filter and two 0.027 mm lead screens. The sample with a mean OD of 1.66 has been digitised with a pixel size of 6.662 μm and a randomly chosen area of $500 \cdot 500$ pixels was investigated. The GLCM of original and artificial noise are investigated by visualising them in Figure 4.8. To facilitate interpretation, the grey level range of the noise images was downsampled/quantised by a factor of 10 (1 grey level unites 10 grey levels of the pre-scaled image) before calculating the GLCM. This results in a smaller and less sparse GLCM. The offset used for assessing the behaviour is set to (0,1) in order to investigate neighbouring pixels. The resulting GLCM of both the original and artificial noise are very similar. To quantify further, including when many offsets in the GLCM are considered, specific features can be extracted. To do this, the original grey level range was used for the noise images. Figure 4.9 shows the contrast feature of the GLCM for various offsets in one direction. Because the noise is directionally independent, it is sufficient to consider offsets in one direction only. The original noise and noise simulated by the random phase method lead to almost the same values of the statistical contrast measure for a specific offset. The statistical properties for white Gaussian noise have been compared additionally. They differ strongly from the original and realistically simulated noise. White Gaussian noise leads to a constant contrast value over all offsets of around $9.7 \cdot 10^6$, which is significantly different from both the true and

artificial noise. The constant value is expected since there is a lack of correlation between any pixels.

Other features of the matrices such as energy, correlation and homogeneity have been compared leading to analogous results. Hence, it can be stated that noise generated by the presented method is statistically not distinguishable from original noise.

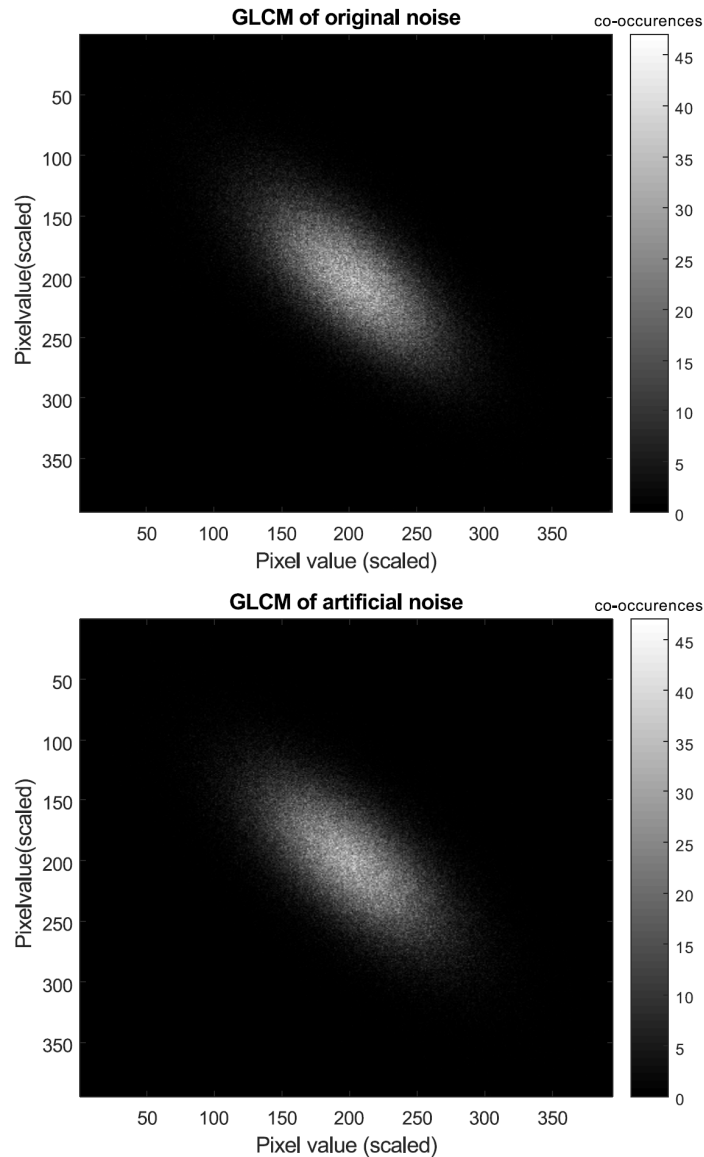


Figure 4.8 *GLCM of original and artificial noise whereas the image grey levels are downscaled by factor 10*

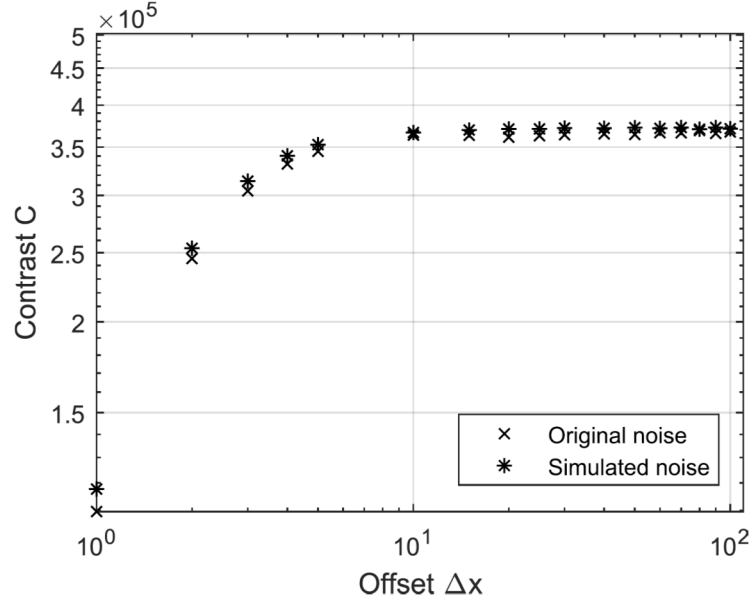


Figure 4.9 *GLCM contrast feature of original and simulated noise for various offsets Δx ; white Gaussian noise leads to a constant contrast value over all offsets of around $9.7 \cdot 10^6$*

4.5 Conclusions

A new, non-stationary film noise simulation method was presented in this chapter based on experimental noise spectra. The procedure enables non-stationary noise with space-varying spectral characteristics to be modelled by a segmentation approach, while assuring the correlation between pixels of different segments. No borderlines become visible because internal correlation between pixels is maintained throughout the image. The artificial noise is characterised locally by having the same spatial frequency contents and distribution as the experimentally obtained homogenous reference noise. Additionally, a simplification of the algorithm is presented, which is applicable if the noise can be assumed to have a Gaussian distribution and if the Noise Power Spectrum (NPS) is collinear.

Application and validation of the method were performed with an example from industrial radiography. Experiments were carried out by an optical setup to deduce spectral properties of various original noise samples on radiographic film. The characteristics of film noise (collinearity of the NPS and Gaussianity of the noise distribution can be assumed) enable the application of the simplified version of the noise generation method for film noise. In this case, the non-stationarity of the noise is not relevant apart from the local standard deviation of the noise. The generated noise is visually and statistically indistinguishable from the reference material and shows similar graininess, which was shown in various validation studies. The final images appear very natural.

The presented model marks important progress in film noise simulation since it does not suffer from drawbacks which by default are intrinsic totally or partially to the methods described earlier. The new model

- considers the whole spatial spectrum of experimental film noise data and does not rely only on a single or a few parameters,
- incorporates signal-to-noise correlation locally by a space-varying, non-stationary approach,
- considers internal spatial correlation to simulate grain clusters,
- generates new and unique noise patterns for the whole image every time it is applied,
- does not assume Gaussianity of the film noise in its general version,
- and is computationally cheap.

The results of the new film noise model will improve the simulation e.g. of X-ray images in industrial radiography significantly. Being a major obstacle in detecting

visual signals in practice, realistically modelled film noise allows an important step forward to be made for industrial radiography simulations. Furthermore, the presented model will be valuable for the movie and photo industry interested in adding a realistic analogue film noise graininess feeling to the digital noiseless productions. This is an application area outside the scope of this thesis. It will be fruitful for any field where a space-varying, statistically non-stationary noise model based on local spectral characteristics and probability density function is desired. The following chapter presents a method describing how the necessary input data for the noise model can be determined experimentally.

Radiographic film system classification and noise characterisation by a camera- based digitisation procedure

In this chapter, a new method for digitising radiographic films on the microscale is presented that enables the generation of experimental input data that is necessary for the noise model presented in Chapter 4. The chapter starts with an introduction of film assessment and a theoretical description of important film noise characteristics. Afterwards, a new optical-based digitisation procedure is described. This was mainly developed by Dr Uwe Zscherpel at BAM and improved as well as put into operation within this PhD project. In this chapter, it is shown that the Optical Density values and the film granularity measure can be correctly extracted from real film samples by the method. Furthermore, the described statistical characteristics of film noise are experimentally validated by means of the presented inspection procedure. Importantly, the new method enables the statistical characteristics of film noise that serve as an input basis for the noise model introduced in the preceding Chapter 4 to be extracted. Moreover, two additional practical applications that rely on the new digitisation method are demonstrated and validated: the method can replace traditional microdensitometer measurements for characterising the film system as well as being used to measure the film system unsharpness.

The work presented in this chapter is submitted as a research paper to NDT & E International [9] and the chapter follows the structure of the paper.

5.1 Introduction

As outlined in the previous Chapter 4, analogue films are still widely used in the industrial environment for capturing the radiographic image and regular assessment of the film systems in order to ensure that they meet the quality standards [13] is necessary. Film characteristics such as film noise (e.g. granularity) or inner film system unsharpness affecting the image quality are evaluated. Currently, the assessment of film granularity is performed by time-consuming pointwise microdensitometer measurements, which therefore provides a significant need for a technique which could evaluate the film more efficiently. This data can also be valuable in other areas, for example in the realistic simulation of film noise, which is based on accurate film noise characteristics from real film samples [8]. The reader can refer to Chapter 4 of this thesis for an in-depth presentation of film noise modelling.

In the present chapter, a new procedure for evaluating radiographic film systems is presented. The method is an approach to achieve the correct digitisation of the film. It consists of a setup based on an optical camera and an image processing procedure enabling radiographic film images and film noise to be digitised.

In order to validate the method, statistical properties of film noise are derived theoretically, and it was confirmed that these match the statistical properties extractable from the gained digital data of the real film. Furthermore, a comparison with microdensitometer measurements of the investigated film samples validates that the presented method can achieve the same results with

significantly less cost and time. Another application of the method presented in this chapter is the measurement of the inner film system unsharpness. It is shown that the measurement results are in accordance with the literature data and this comparison, therefore, provides a further validation basis of the introduced digitisation approach.

In section 5.2, film noise characteristics such as Gaussianity of the Optical Density (OD) fluctuations and spatial spectral properties are theoretically derived. The optical setup including the measurement procedure is presented in section 5.3 followed by results and validations in section 5.4. Applications of the method such as film system classification and the measurement of the film system inherent unsharpness are described in section 5.5 and 5.6. The chapter is concluded with section 5.7.

5.2 Characteristics of film noise

In order to provide the basis for the study in this chapter, some of the concepts associated with film characteristics are outlined. Firstly, the illumination dependency of the Optical Density is described. Afterwards, this section focuses on two main characteristics of film noise, the Gaussianity of the noise grey value distribution and the collinearity of the Noise Power Spectrum (NPS). These main characteristics will be derived theoretically.

5.2.1 Illumination dependency of the OD

The measured OD of an optical image depends on the manner of illumination. Diffuse light leads to a lower measured OD than specular light when using scattering media such as radiographic silver films, and this is an important

consideration with the two main established techniques for measuring OD. Figure 5.1 illustrates the two different densitometry techniques. The incident parallel light beam scatters at the film which acts as a diffusor. A standard macro densitometer measures with directional light illumination in a 10° cone beam (see ISO 5-2 [15]) and detects all diffuse light transmitted through the film (see Figure 5.1 a). In contrast, a microdensitometer measures the specular light due to the low numerical apertures of the used microscopic lenses (see Figure 5.1 b). The scattered light will not be recorded leading to an increased difference between incident and transmitted light intensity (see Figure 5.1 b). This results in a higher measured value of the OD compared to the measurement with diffuse light. Consequently, the OD measured by a microdensitometer usually needs to be corrected by a factor to become comparable to the measurement results of a standard densitometer. This factor is named after André Callier who established a correction approach for OD measured using specular light [81]. Typically, both Optical Densities are correlated by a Callier factor Q_C larger than 1. Q_C ranges between 1.2 and 1.4 for microdensitometers.

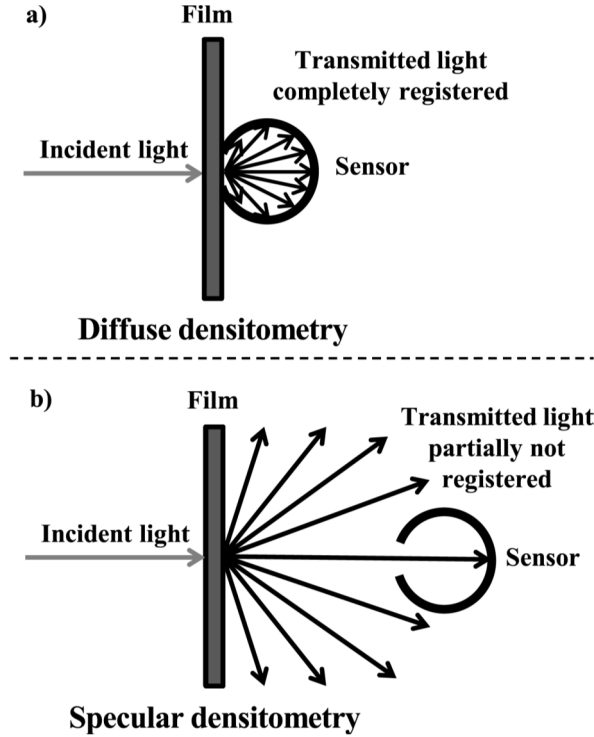


Figure 5.1 *Schematic of diffuse densitometry (a) and specular densitometry (b)*

5.2.2 Theoretical derivation of Gaussian distribution

While exposing industrial radiographic film homogenously with X- or γ -rays, each photon is independent of each other and hence the photons are independently and identically distributed. The photon radiation is characterised by quantum statistics resulting in Poisson distributed noise [12]. For the Poisson distribution, the variance is equal to the expected value of the random variable

$$\sigma^2 = E(N) \quad (5.1)$$

with σ^2 as the noise variance and $E(N)$ as the expected value for N quanta. It can be supposed that the radiation $E(N)$ by N_A photons within an area A results in n_A exposed particles in the area A which is proportional to the number of exposing quanta

$$n_A \propto N_A. \quad (5.2)$$

It is expected that the optical film density OD (above fog and base) is proportional to the number of exposed particles n_A as described by the Nutting formula [60], [64]

$$OD \propto n_A \quad (5.3)$$

which leads to the proportionality

$$OD \propto N_A \quad (5.4)$$

and

$$\sqrt{OD} \propto \sigma. \quad (5.5)$$

This last relationship is known as the Siedentopf relationship [64]: the OD density of a specific area is proportional to the squared standard deviation σ in that area.

It can be supposed that a very large number ($E(N) \rightarrow \infty$) of photons are emitted during the exposure. Under consideration of the Central Limit Theorem, it can be concluded that the photons N_A , which are Poisson distributed, tend towards a Gaussian distribution. Therefore, the proportionality $OD \propto N_A$ implies that the OD tends also towards a Gaussian distribution.

5.2.3 Theoretical explanation of NPS collinearity

Spatial correlation within film noise can be characterised by the application of the 2D Fourier transform, as already introduced in Chapter 4 of this thesis and recalled here. The resulting Noise Magnitude Spectrum (NMS) describes

quantitatively the spatial correlation information of the noise caused by X- or γ -ray radiation mottle and clustering of film grains. In its squared form, the NPS is known as the 2D Noise Power Spectrum (NPS) or sometimes referred to as the Wiener Spectrum

$$NPS(u, v) = \lim_{X, Y \rightarrow \infty} \left\langle \frac{|\mathcal{F}_{2D}\{N_{OD}(x, y)\}|^2}{(X \cdot Y)^2} \right\rangle \quad (5.6)$$

with $N_{OD}(x, y)$ representing the noise image in OD values in the spatial coordinates (x, y) , X, Y are dimensions of the noise image and (u, v) are the spatial frequencies in both Cartesian directions. As already stated in Chapter 4, the Wiener-Khinchin theorem leads to an important property of the NPS: the integral of the NPS represents the variance σ^2 of the noise's OD fluctuations [64]

$$\sigma^2 = \iint NPS \, du \, dv. \quad (5.7)$$

Therefore, the NPS is dependent on the underlying mean OD because of the Siedentopf relationship

$$\iint NPS \, du \, dv \propto OD. \quad (5.8)$$

NDT films are practically only used in the linear regime of the characteristic curve between exposure and OD without an occurrence of saturation effects [12]. Theoretically, a single X-ray photon would expose a cluster of grains leading to a very low mean OD with its own NPS. It is expected that exposure with many independent photons leads to an accumulation of these spectra whereas the magnitude spectra are summable and the shape of the NPS is independent of the mean OD. In other words, the NPS is collinear and scalable in relation to the underlying OD. The OD and therefore the number of interacting photons per film

area only has an influence on the standard deviation but not on the spectral form of the noise.

5.3 Optical setup and measurement procedure

The following paragraphs describe the new experimental setup and procedure for digitising radiographic films. The noise is then evaluated from these digital images. Additionally, the exposure conditions for the film systems used to test the method are described in this section.

Images of the film are acquired by an optical setup consisting primarily of a digital camera, a filter, and an objective lens. This new optical setup was mainly developed by Dr Uwe Zscherpel at BAM but adjusted and originally put into practice as well as validated within this PhD project. The film sample to be investigated is placed on an illumination table creating a diffuse Lambertian illumination (see ISO 10505 [82]) using a plastic diffuser and a white LED with a colour temperature of 2850 K. It is important that this specific illumination is consistent with the standardised OD measurement procedure. Only a small area of the film is imaged to reduce scattered light, which is achieved by placing an opaque mask with a circular aperture on top of the film sample. The aperture diameter is set to 8 mm, which is selected as a good trade-off between minimising scattered light reduction while maintaining a reasonably sized region of interest. The setup further consists of a $V(\lambda)$ -filter (see ISO 5-3 [16]) in order to simulate the spectral sensitivity of perceiving luminosity by the human visual system in daylight. This filter is crucial in order to achieve good results. The filtered light is focused by an objective lens (Rodestock, Rogonar-S 75 mm) mounted on a bellows device to achieve a magnification of 1:1.92 and captured by a digital

camera (Model name: Basler acA4112-20um). The CMOS sensor (Model name: 1/1" IMX 304 Sony CMOS Sensor 12 bit Monochrome) of the camera has a resolution of 12.4 MP (pixel size on-chip: $3.45\text{ }\mu\text{m}$) leading to an effective measured pixel size of $6.62\text{ }\mu\text{m}$ in the acquired images. The pixels on the chip are back-illuminated for increased low-light performance (the light strikes the photodiode layer from the back to avoid interference from the wiring of the layer). Additionally, the sensor performs an automatic dark correction. For a specific exposure time and temperature, this correction reduces camera-induced image noise by subtracting the dark signal measured when the pixel was not illuminated. The objective lens and the camera are replaceable by other models if different magnifications and resolutions are to be achieved. However, the described automatic camera-specific corrections need to be performed manually or in the subsequent image processing steps if they are not supported by the chosen camera model. When taking measurements, the complete setup is placed into a lightproof case to prevent interaction with ambient light. The optical setup is shown in Figure 5.2.

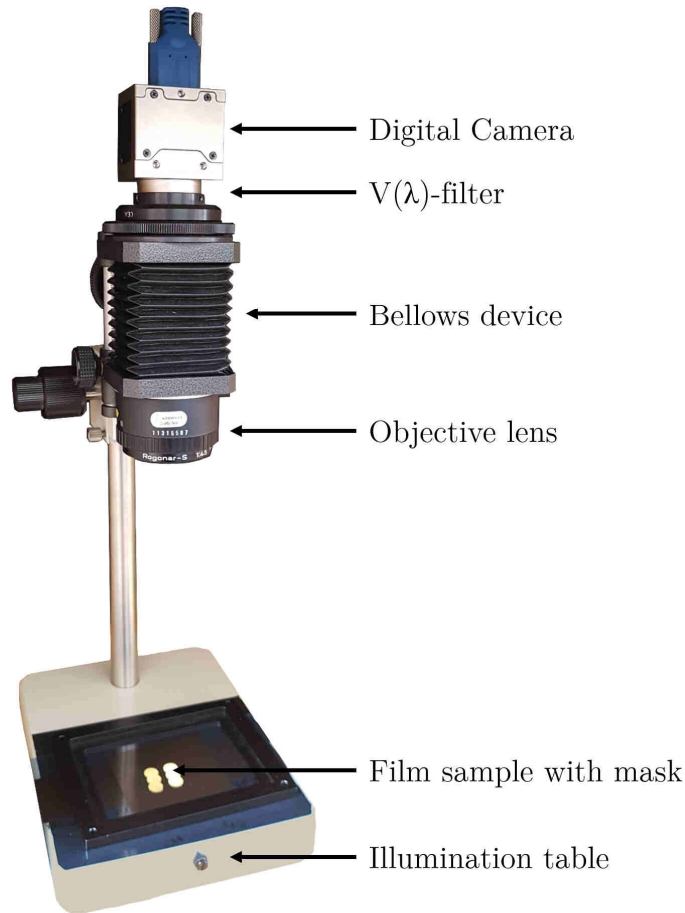


Figure 5.2 *Optical setup for film digitisation*

The live image is acquired and processed by a special ImageJ plugin module for control and averaging of Basler cameras [83] within the programme ImageJ [84]. The sharpness of the final image is crucial. To maximise the sharpness, the standard deviation of a Region Of Interest (ROI) histogram of the live image is monitored and the lens focus is manually adjusted so that the standard deviation in the ROI is maximised. In order to capture images that are not affected by photon noise of the illumination light, each measurement consists of 400 frames that are taken and arithmetically averaged. The exposure time of a single frame is manually chosen in relation to the transparency of the investigated film sample, usually between 10 and 400 ms. Less transparent samples need longer

exposure times in order to capture enough photons whereas more transparent film samples are investigated at shorter exposure times to avoid clipping of the measured OD value.

Furthermore, the raw images are calibrated and processed using the commercially available software ISee! [85]. It is necessary to perform a flat field correction to suppress shading of the illumination table and the objective lens, dust in the imaging system and other artefacts. The corrected light intensity in the image I_{corr} is calculated following the formula

$$I_{corr} = \frac{I_{raw}}{ff} \cdot 50000 \quad (5.9)$$

with I_{raw} as the grey valued raw image and ff as the flat field image taken without a film sample placed on the illumination table. The image is scaled to be saved in a 16-bit TIFF format; the factor 50000 is selected as being slightly below the maximum 16-bit integer of $2^{16} - 1 = 65535$ in order to avoid clipping.

Afterwards, the grey value images need to be transformed into Optical Densities. Application of a look-up table operation within ISee! according to the formula

$$I_{OD} = \log_{10} \left(\frac{50000}{I_{corr} + 1} \right) \cdot 10000 \quad (5.10)$$

leads to images representing the OD by integers of $10000 \cdot OD$. The +1 is added to prevent division by zero. The OD images may have an OD offset caused by longer optical exposure times than the exposure time used to take the flat field image ff . A factor of x in the exposure time leads to an OD offset of $\log_{10}(x)$ that must be subtracted from the measured OD. Furthermore, the OD offset caused by the fog and base of the film is also subtracted. The OD of the fog and base of a film can be measured by determining the mean OD of a developed but

unexposed film sample of the same film batch and stored under the same conditions.

5.3.1 Film sample exposure

The film samples serving as the experimental basis of the work presented in this chapter were gained by exposures with both X-rays and γ -rays during placements of the author at BAM in Berlin. The X-ray exposures were performed using a Seifert MB420/10 TitanE X-ray tube and the γ -ray exposures by an Iridium-192 γ -ray source with 11 Ci activity, both 2 m from the film. This distance is large enough to neglect the resulting geometrical unsharpness of 0.002 mm. The investigated films were AGFA STRUCTURIX VACUPAC D4 and D7 of film system class C3 and C5, respectively. Various filters have been placed on the tube port in order to vary the radiation quality whereas the lead screens are always in perfect contact with the film ensured by a vacuum-packed lightproof film package. The exposure setup is shown in Figure 5.3.

The standard exposure setting for the work presented in this chapter is that samples of film system class C3 were exposed by X-rays emitted from a 220 kV tube and filtered by 8 mm Cu using 0.027 mm Pb screens on either side as described in ISO 11699-1 [13] for NDT film system classification.

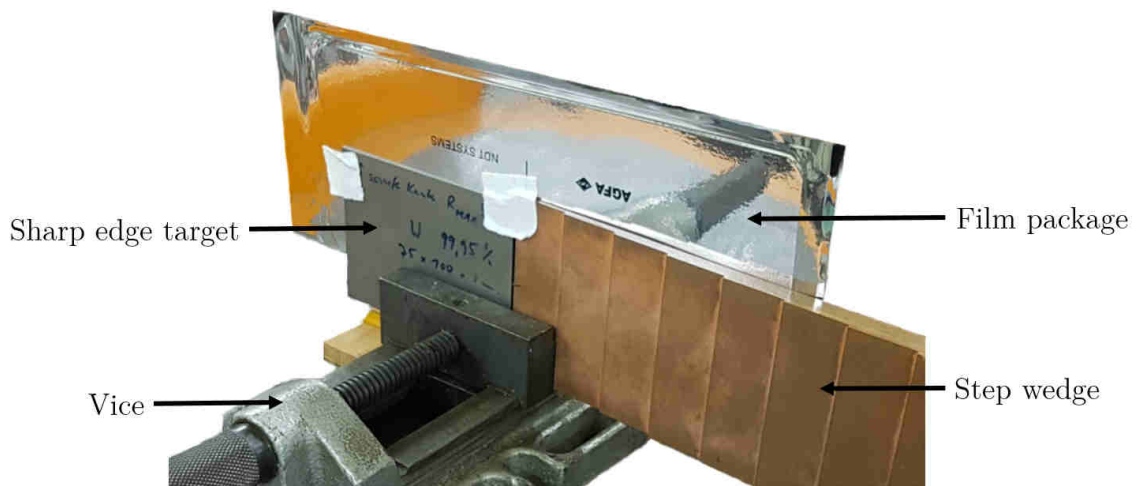


Figure 5.3 *Clamped radiographic film with step wedge (from Cu) and sharp edge target (1 mm W plate)*

5.4 Results and validation

In order to validate the presented method, it is necessary to verify that the mean OD values measured by the new camera-based setup match with measurements of the same film samples using a standard densitometer. Additionally, the film noise characteristics introduced in section 5.2 must be verifiable by the data delivered from the new digitisation procedure. These validations are crucial in order to ensure that the new measurement technique reproduces the expected data correctly (see ISO 11699-1 [13], clause 5.3). Firstly, it will be shown that the OD density is measured correctly. Secondly, the Gaussian distribution of the noise grey values will be shown, and thirdly, the collinearity of the noise NPS will be validated. Therefore, the presented method is capable to deliver the input data that is necessary for the noise model described in Chapter 4. It will also be shown in section 5.5 that the method can replace the traditional microdensitometers to classify film systems.

5.4.1 Diffuse density measurements of the films

As a first validation attempt, the accuracy of the measurement of the visual diffuse Optical Densities using the camera setup shown in Figure 5.2 needs to be verified. ISO 5-2 [15] and ISO 5-3 [16] define the geometrical and spectral conditions for the construction of a standard macro densitometer using a measurement aperture in the range of 2 mm diameter. The camera used in this work has a much higher spatial resolution of about 6.62 μm pixel size. As mentioned above, it is typical for high-resolution microdensitometers to use specular light (see Figure 5.1 b). In this case, the measured OD is higher than the visual diffuse OD measured by a macro densitometer because the optical setup of the microdensitometer does not fulfil the requirements of ISO 5-2 [15]. Therefore, a correction of the specular OD to produce the equivalent diffuse value is usually required as suggested by Callier [81].

It was investigated how much the presented setup needs to be Callier corrected in order to deliver measurement results directly comparable with OD measurements delivered by a standard macro densitometer. A C3 film system was exposed to mean diffuse densities including fog and base of around $\text{OD} = 2 \pm 0.6$. These Optical Densities were measured by a standard macro densitometer and compared with measurements by the new setup of the same areas on the film. The resulting OD above fog and base of the new camera setup as well as the OD measured by a standard macro densitometer (model BAMLEDD1, BAM design according to ISO 5-2 and ISO 5-3 [15], [16]) are displayed in Figure 5.4. These results represent the Callier function of the presented optical setup. According to the equation of the linear regression, the Callier factor of 1.004 is only 0.4 % larger than 1 and can, therefore, be neglected in all further considerations.

This interesting finding is valid for all investigated NDT film systems and allows to measure directly visual diffuse Optical Densities independent of the resolution, i.e. it is valid for 6.62 μm pixels as well as single measurements using a 2 mm aperture.

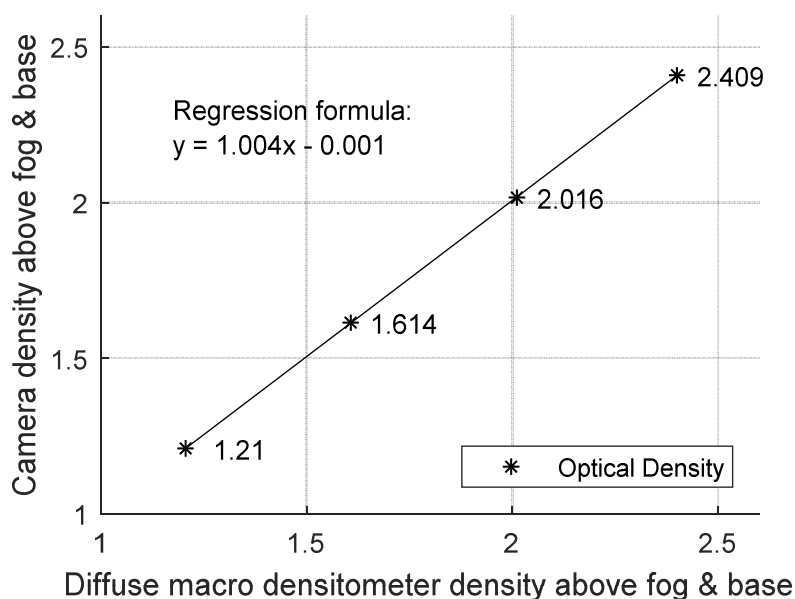


Figure 5.4 *Measured camera densities versus visual diffuse macro densities using a diffuse densitometer*

5.4.2 Gaussian distribution of film noise

As an example, a sample with a mean OD of 1.17 is digitised. A detail of the digitised film sample is displayed in Figure 5.5. To prove that the grey values of film noise have a Gaussian distribution, the grey valued image matrix of the sample has been normalised to a mean OD of 0 and a standard deviation of 1000. Afterwards, the probability density function of the sample is compared with the probability density function of an equally normalised Gaussian distributed array of random values. The result is displayed in Figure 5.6. It can be clearly seen that the grey values of the film sample are Gaussian distributed. Consequently,

the theoretical statement of section 5.2.2 has been validated by means of the presented optical setup.

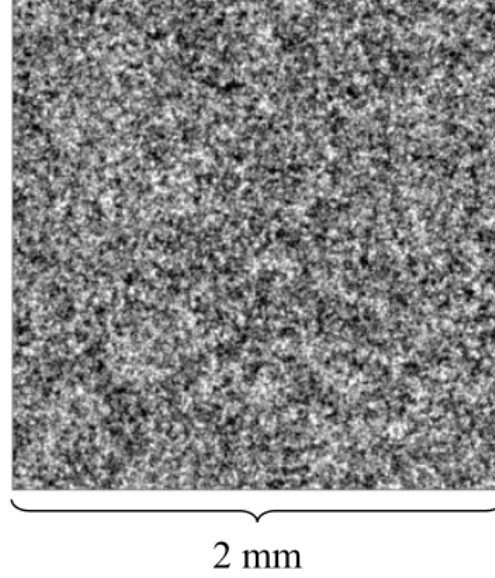


Figure 5.5 *Detail of film noise sample, side length 2 mm (pixel size of $6.62\ \mu\text{m}$)*

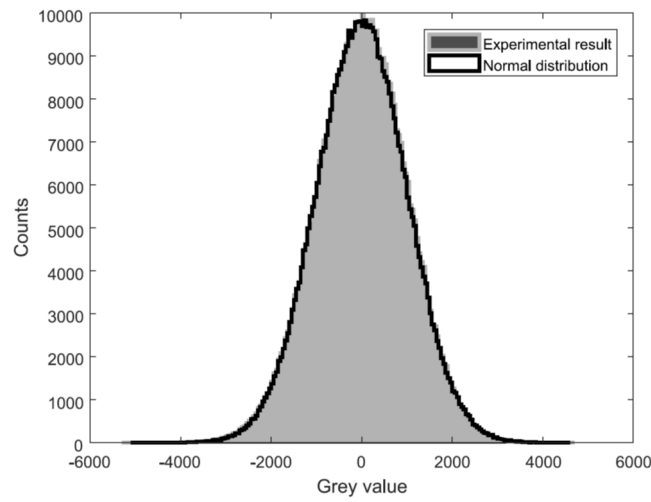


Figure 5.6 *Comparison of normalised probability density functions of real film noise sample and Gaussian distributed noise; grey values are coding according to equation (5.10) the measured optical film densities*

5.4.3 NPS investigations

Homogenous film samples exposed by different radiation energies to a mean OD of 2 are digitised and the NPS is calculated and compared. Exposures with γ -rays by an Iridium-192 source (with lead screens on the film) and X-rays (220 kV with lead screens and 90 kV without lead screens) are performed. A squared area of 18.5 mm ($2800 \cdot 2800$ pixel) was investigated providing a large enough sample area for high spectral resolution. The NPS can be resolved reliably up to 40 line pairs/mm (lp/mm). Theoretically, the setup should resolve up to 75.53 lp/mm with a pixel size of 6.62 μm , but this is practically not achievable because of an imperfect optical transfer at high spatial frequencies. Extracting the optical transfer function is a significant challenge at these higher frequencies, closer to the resolution limit. The resulting NPS are plotted in Figure 5.7. Two noise components are discernible in the spectral representation. The NPS is flat and horizontal towards higher spatial frequencies which can be interpreted as white noise caused by film graininess. However, a peak is distinguishable from the flat spectrum towards lower frequencies. That peak of low frequency noise is caused by remaining shading on the noise sample (the sample is not perfectly homogenous) and also caused by low frequency noise due to radiation mottle resulting from spatial fluctuations of the exposing photons [86]. Higher exposure energies cause stronger radiation mottle and therefore the low frequency part of the NPS is more pronounced when exposing with high energetic γ -rays than exposing with less hard 220 kV X-ray radiation or even less hard 90 kV X-ray radiation.

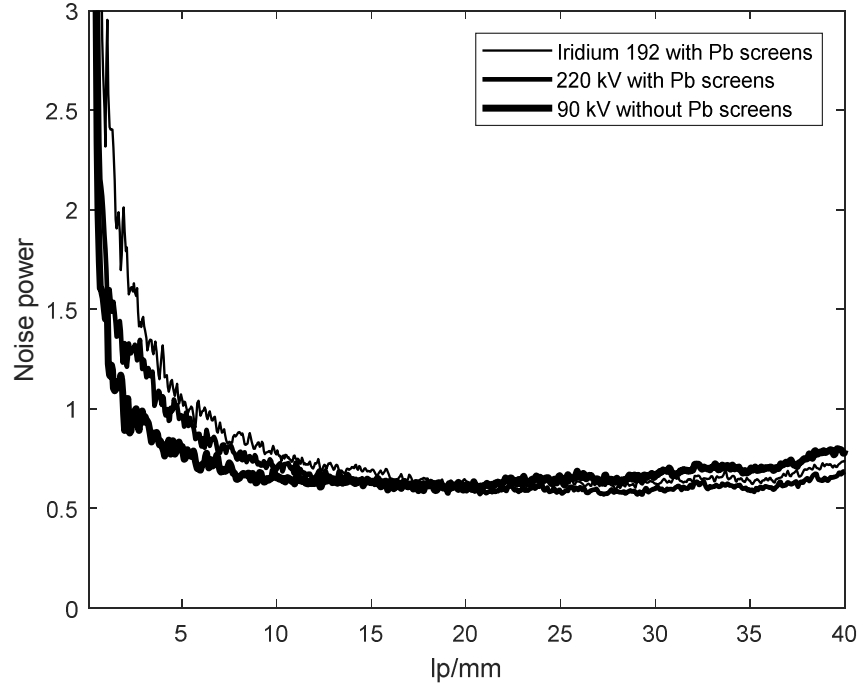


Figure 5.7 *NPS of homogenous film samples exposed by different energies to a mean OD of 2*

The Wiener-Khinchin theorem states that the NPS of the fluctuations of a stationary ergodic process (which is the case for homogeneously exposed films) is the Fourier transform of the autocorrelation function of these fluctuations [64]. Films exposed homogeneously under the same conditions but with different mean ODs have been investigated in order to validate the collinearity of the NPS for a specific case of exposure energy. The noise image is firstly normalised to a mean OD of 0 by subtracting the mean OD because only the OD fluctuations are of interest. Furthermore, the image is normalised to a standard deviation of 1 by dividing by the standard deviation of the original image. The 2D autocorrelation $Z(k, l)$ of the normalised noise image $N_{norm}(x, y)$ is calculated by

$$Z(k, l) = \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} N_{norm}(x, y) N_{norm}(x - k, y - l) \quad (5.11)$$

The autocorrelation is further normalised to

$$Z_{norm}(k, l) = \frac{Z(k, l)}{\max_{k, l} Z(k, l)} \quad (5.12)$$

It was investigated if the normalised autocorrelation coefficients of film noise with different mean OD are equal, as suggested by Dr Nicolas Paul from EDF. To test this, film samples with a mean OD of 1.7 and 3.8 have been digitised. The correlation coefficients are investigated of an arbitrarily chosen area of $700 \cdot 700$ pixels in either film sample. The normalised autocorrelation coefficients which are unequal to 0 are plotted in the top left and top right part of Figure 5.8 for comparison. A cross-section comparison of the normalised autocorrelation coefficients for either mean OD at a vertical pixel position of 0 (indicated by small arrows in upper graphs) is displayed in the lower graph of Figure 5.8 to facilitate the comparison. The normalised autocorrelation coefficients are almost identical for both film samples of different mean OD. This demonstrates that the statistics of the noise are identical for noise with different mean ODs apart from the standard deviation. Consequently, the NPS can be scaled according to the formula

$$NPS_{target} \equiv \left(\frac{\sigma_{target}}{\sigma_{basis}} \right)^2 NPS_{basis} \quad (5.13)$$

with NPS_{basis} as the NPS basis from which it shall be scaled to the target NPS_{target} , σ_{basis} as the standard deviation of the scaling basis image and σ_{target} as the standard deviation of the noise image with target NPS. This scaling maintains the NPS shape and changes only the area under the NPS, which represents the standard deviation. With this property proven, it is possible to

calculate the NPS for noise with any underlying mean OD when only one NPS for the specific exposure case is available.

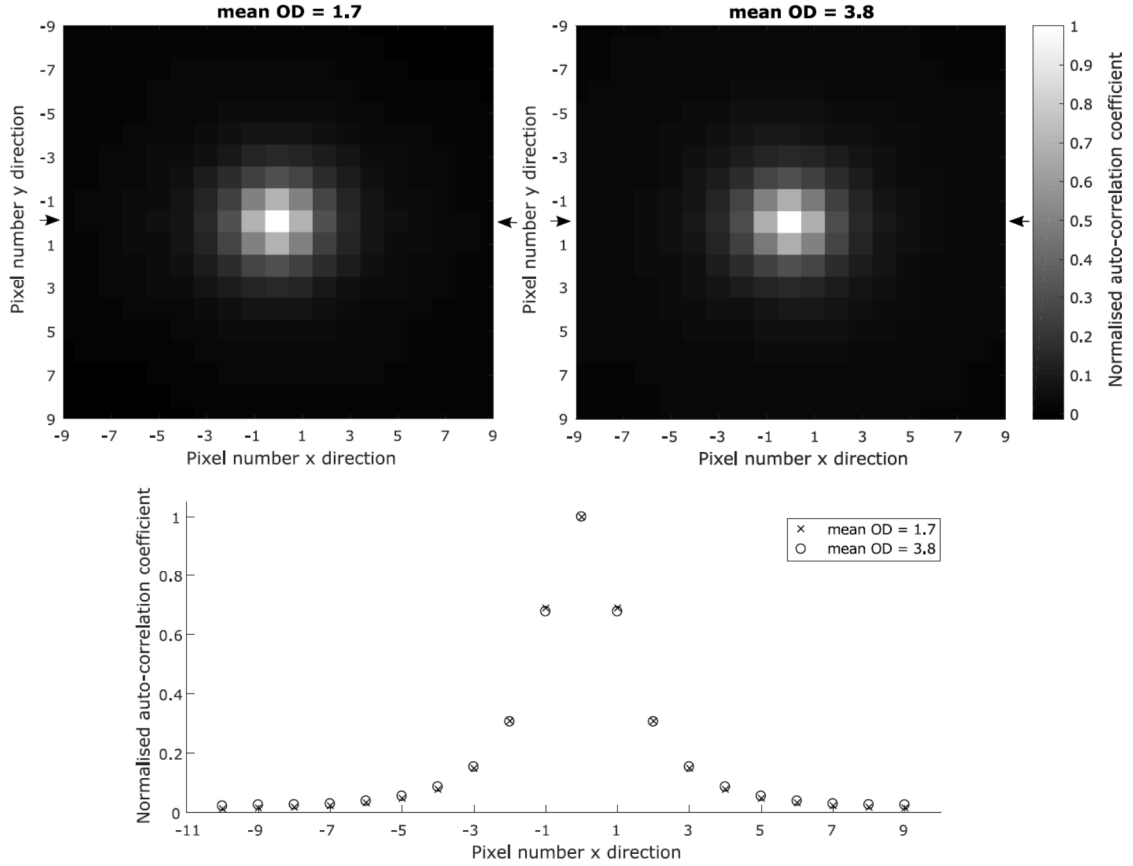


Figure 5.8 *Normalised autocorrelation coefficients of film noise with mean OD of 1.7 (top left) and mean OD of 3.8 (top right) including a comparison of the cross-section values at vertical pixel position of 701 (bottom plot)*

5.5 Application 1: Replacement of microdensitometer for film system classification

This section is dedicated to demonstrating that the presented optical setup can effectively replace microdensitometer measurements for film system classifications according to ISO 11699-1 [13]. Firstly, no correction of the measured diffuse

density values is necessary, because this optical setup for camera-based microdensitometry fulfils all requirements of ISO 5-2 [15]. Therefore, any Callier correction is not necessary. Secondly, a procedure for correcting the measured standard deviation is presented. This is necessary because the optics influence the measured granularity. Afterwards, the measurement procedure is validated by comparing against standardised measurement results using a scanning microdensitometer.

5.5.1 OD standard deviation correction

The calibrated camera OD images show the same OD values as those obtained using a standard microdensitometer with Callier correction. But the measured standard deviation of the OD of steps with homogeneous density measured by the camera setup is around 20 % lower than the standard deviation measured by a microdensitometer after Callier correction (see ISO 10505 [82]). The next paragraph describes how the standard deviation is corrected.

As it is the case for each optical imaging system, the experimental setup consisting of the camera and objective is characterised by a specific Optical Transfer Function (OTF) and the corresponding absolute part, the Modulation Transfer Function (MTF) describing the optical system behaviour. When imaging an object, the amplitude of higher spatial frequencies is reduced, which is equivalent to applying a smoothing filter. The MTF is a function of the amplitude reduction over spatial frequency. This amplitude reduction leads to a loss of detail which is quantified by the MTF. Image smoothing by the optical MTF causes an undesired reduction of the standard deviation of the OD in the image while taking measurements. As a result, the OD standard deviation is reduced compared to the standard deviation measured by a microdensitometer

after Callier correction. The microdensitometer measurement is not affected by an optical MTF because only contrastless pointwise OD measurements of non-overlapping film regions are taken and no imaging is performed. In order to remove the influence of the optical MTF by the camera setup, the image needs to be deconvolved of that optical MTF. This procedure is described in the following paragraphs.

Firstly, the 1D MTF of the imaging system needs to be determined. This MTF is mainly influenced by the used objective lens and needs to be re-evaluated when the lens is changed. A sharp-edge target (a chromium-plated rectangle on a polished glass plate) is imaged and the grey-scale value image is transformed into OD values. A line profile of OD values perpendicular to the sharp edge is then taken, called Edge Spread Function (ESF). In practice, around 30 of these line profiles are averaged to improve the Signal to Noise Ratio (SNR). The first derivative of that averaged profile is the so-called Line Spread Function (LSF). The Fourier transform of the LSF is calculated and the normalised magnitude of this Fourier transform is the 1D MTF [87].

Given that isotropy of the imaging system sharpness is assumed, it can be supposed that the optical MTF is identical in all directions of the 2D image. For this reason, the 1D optical MTF can be expended to the 2D space by turning the 1D MTF 360 degrees around its origin. No data is available for frequencies higher than stored in the 1D MTF, which could be problematic for the components located within the corners of the 2D plane. In these areas, an MTF value of 1 is assumed which means that no correction is done where no MTF data is available. However, this is likely to have minimal impact because the majority of spectral content will lie at much lower spatial frequencies. Afterwards, the 2D FFT of the OD image is calculated and divided by the 2D optical MTF in the Fourier space

in order to perform the deconvolution. The result is transformed back in the spatial domain by an inverse FFT calculation. The resulting image cannot be regarded as a real image as the phase information has no physical meaning; instead, the image is used just to calculate the OD standard deviation as measured by a microdensitometer after Callier correction, which is possible because the standard deviation is independent of the phase of the image. The deconvoluted image needs to be reduced in resolution to be in accordance with the sampling resolution of the microdensitometer of 88.622 μm pixel size (for a quadratic aperture or 100 μm diameter for a circular aperture, see ISO 11699-1 [13]). An image resizing algorithm is chosen that averages values of neighbouring pixels using a box-shaped kernel. The correct standard deviation according to ISO 11699-1 [13] results from independently calculating the standard deviations along 55 image lines of 20 pixels length and taking the median of these results.

5.5.2 Validation of granularity measurement

The standard deviation of the OD fluctuations in a uniformly exposed film emulsion is a measure of film “granularity”. Granularity is a measure to quantify objectively the film noise. ISO 11699-1 [13] defines a specific measurement procedure and tables maximum granularity values for various film system classes. In order to validate the film noise digitisation procedure, granularity measurements in accordance with ISO 11699-1 [13] are performed using the data provided by the experimental setup with the application of the MTF correction procedure described above. The measurement results are compared with the reference granularity values published in ISO 11699-1 [13]. That standard tables maximum granularity values for specific film system classes. According to the standard, the granularity measurements must be performed in a film region with a mean OD of 2 above fog and base to be comparable. These maximum values

should not be exceeded if the film system shall meet the requirements of the specific class. Hence, the investigated film system should be characterised at a mean OD of 2. In the practical application, a film with such a specific mean OD is often not available. For that reason, ISO 11699-1 [13] allows the granularity value for a mean OD of 2 to be interpolated using three or more film exposures at different density levels around $OD = 2$. The interpolation is performed by a linear regression analysis of the granularity as a function of the square root of the density. The film system classes C1, C3 and C5 have been investigated here. Figure 5.9 shows the measured granularity after MTF correction and the maximum granularity values listed in ISO 11699-1 [13] including an acceptable tolerance of +10 %. The measured granularity values are in the granularity range of the specific film system class. For comparison, BAM provided reference measurements by a microdensitometer (model Joye-Loebl 3CS with upgraded data acquisition based on a Raspberry-Pi computer) using the same film samples. These experimental reference measurements are added to Figure 5.9 and they are slightly higher than the measurements of the presented work which can be explained by additional noise within the microdensitometer. This comparison validates the presented optical setup and procedure to measure granularity values correctly.

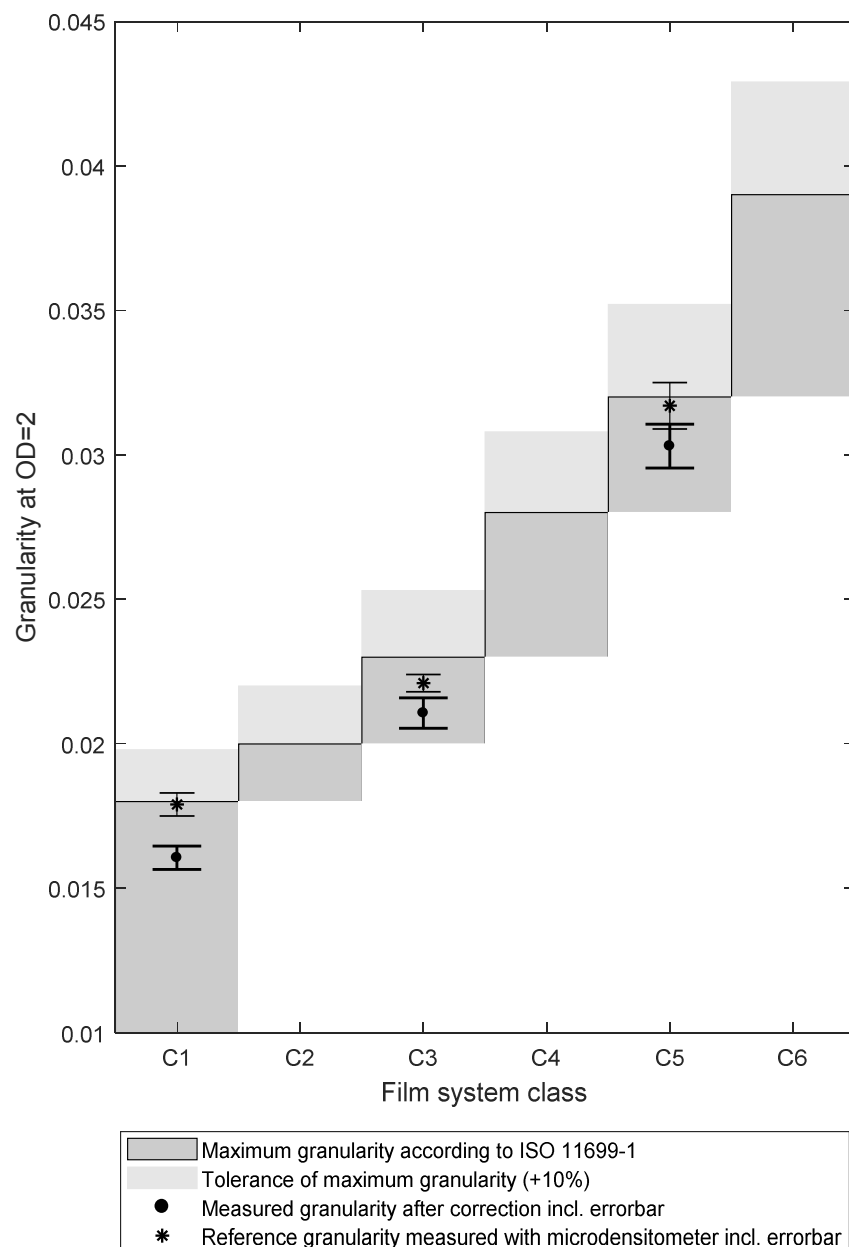


Figure 5.9 Granularity measured by the new experimental setup and maximum granularity according to ISO 11699-1 [13]

5.6 Application 2: Measurement of film system inherent unsharpness

In industrial radiology, high energetic X- or γ -ray photons are absorbed by the lead screens in direct contact with the film emulsions. Above 80 keV, lead screens generate secondary electrons which activate the seeds of the latent image in the film emulsion. These photoelectrons travel within the film emulsion depending on their energy and make a string of silver bromide (AgBr) grains developable along their travel path. Hence, during exposure, not only a single AgBr crystallite becomes developable, but a cloud of grains. This results in a blurring of the image: the definition is limited by the travel distance of the secondary electrons. Exposure with higher energy results in higher energetic secondary electrons and therefore longer travel paths and increased unsharpness. This unsharpness is called inherent or film system unsharpness U_f [4].

The inherent unsharpness is described by the MTF of the film system (not to be confused with the optical MTF of the camera system). The film system MTF depends on the used metal screens and the development conditions as well as the specific exposure conditions defining the photon energy, such as the radioisotope or tube voltage and filters. The inherent unsharpness is measured by the Klasens' method [88]. This method allows the inherent sharpness on the radiograph of a knife-edge target to be measured, however, to do this it must be assured that geometric and motion unsharpness are negligible in order to measure solely the film system unsharpness. The sharp edge becomes blurred on the film and the width of the band of blurring can be seen as a measure of the inherent unsharpness. To measure the width of the blurring band, an OD profile

orthogonal to the OD transition area is investigated by application of the Klasens' method [88].

A 1 mm tungsten plate in direct contact with the film pack is used as a knife-edge target to expose a sharp edge on the film. The film-to-source distance is 2 m which is large enough to neglect the geometrical unsharpness of 0.002 mm (given a focal spot size of 4 mm). Additional exposures have been made using a lower tube voltage of 90 kV with a 30 mm thick Al filter and γ -rays from an Iridium-192 source with 11 Ci activity.

The film system unsharpness is measured and compared to the literature values given in [4]. Figure 5.10 shows the measured inherent unsharpness as well as literature values for various beam energies. It is observable that the measured results are very good in accordance with the literature. Therefore, it can be concluded that the optical digitisation system provides correct data for measuring efficiently the film system inherent unsharpness and accordingly also NPS spectra dominated by this MTF.

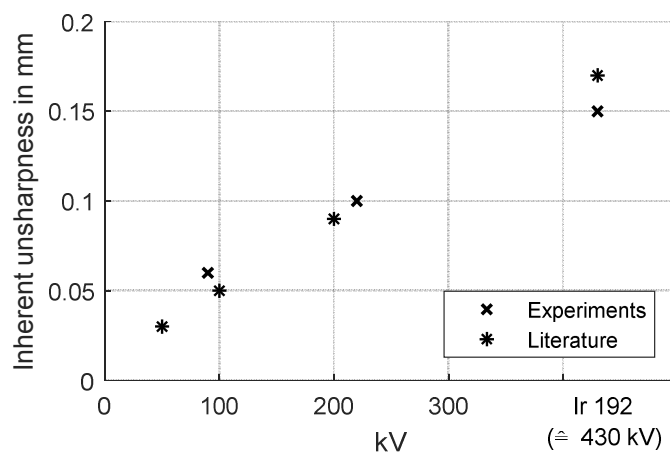


Figure 5.10 *Comparison of measured inherent unsharpness with literature values from [4]*

5.7 Conclusion

A new setup based on an optical camera has been introduced to investigate exposed and developed industrial radiographic film systems. Specific characteristics of industrial radiographic film systems have been theoretically described and experimentally validated by the presented methods. Furthermore, it was shown that the method enables film systems to be classified correctly when applying the presented correction algorithm, and therefore can replace the state-of-the-art classification procedures using a microdensitometer. This will make the classification process much more efficient. It was also demonstrated that the method correctly measures the film system inherent unsharpness for various exposure conditions.

The presented setup can also be used as a simple validation tool for archived films to verify the film system class which was required by the corresponding standard at film exposure. The film system class is determined by the ratio of the film gradient at $OD = 2$ and the granularity at this density. This camera-based setup can measure both at the same time in the same homogeneous film area. Therefore, the film system class can be determined easily, even after years of storage.

Conclusions

In this concluding chapter, a short review of the thesis is given summarising the work conducted during this PhD project. This chapter also includes a presentation of the main scientific contributions as well as an outlook on possible future work and implementation projects currently ongoing in industry.

6.1 Review of the thesis

The thesis started with an introduction in Chapter 1 giving an overview of the industrial context to the presented work as well as a concise insight of the main NDE techniques. It enabled the reader to see the problems in a broader context and to understand the organisation of this PhD project.

Chapter 2 focused on giving background information on radiographic testing, the main NDE technique of interest for this thesis. This section was followed by an introduction of the Fourier transform in 2D, which is a crucial mathematical operation and an important tool for the image processing tasks dealt with in this thesis.

Automating the assessment of radiographic images is an important step to improve radiographic test procedures. Therefore, Chapter 3 introduced a new visibility criterion based on the Channelized Hotelling Observer (CHO), which has been proven to correctly assess the quality of simulated radiographs.

Noise plays an important part in the simulation chain of radiographic images. Chapter 4 presented a new model for simulating realistic film noise that is based on experimental investigations of real noise samples. The noise generated by the model was validated to be visually as well as statistically indistinguishable from real noise.

How these experimental investigations of real film samples serving as an input basis for the new noise model have been performed was presented in Chapter 5. It introduced a new optical setup to digitise film samples on the microscale. The digitisation procedure was validated and further practical application areas for the setup have been described and it was confirmed that the setup is very effective in performing these tasks such as measuring the film system granularity and unsharpness.

6.2 Main contributions

In this section, the main scientific contributions achieved during this PhD project are listed. The contributions are allocated to the correspondent chapter of this thesis.

The main research results obtained in Chapter 3 are:

- *It was the first time (to the author's knowledge) that the CHO has been used in NDE to assess the image quality within industrial radiography. The modelled observer measures objectively the quality of simulated radiographic images relying on the prediction of the human observer detectability of flaws.*

- *The implemented CHO was validated by comparing the efficiency of the model to other visibility models and standards as well as psychological data.*
- *It was shown that the new method outperforms existing models in industry.*
- *This new visibility model can replace the manual image assessment previously undertaken by an operator in the simulation chain.*

The main research results obtained in Chapter 4 are:

- *A new model to simulate 2D random noise fields with spatially heterogeneous statistical properties such as local, space-varying spectral characteristics and probability distributions was developed.*
- *The noise generated by that original method relies on real experimental data and not on artificial parameters as it is the case for most other existing noise models.*
- *The correlation between noise and image as well as the internal correlation of the noise throughout the image is ensured by the presented simulation method.*
- *The new method enables the simulation of noise with local and realistic granularity as well as contrast.*
- *The benefits of the presented model are the fast generation of unique noise samples, the exploitation of real experimental data and its statistical non-stationarity. The combination of all these benefits is not available by other noise models published in the existing literature.*

- *The new model improves the realism and value of radiographic image simulations enabling more realistic assessments of radiographic test setups.*
- *The presented technique is general and its use is not restricted to industrial radiography but goes far beyond and will be useful for areas such as photography or the movie industry or whenever the generation of 2D noise with local, space-varying statistical properties is desired.*

The main research results obtained in Chapter 5 are:

- *A new optical-based digitisation procedure was described, improved as well as put into operation for digitising radiographic films on the microscale.*
- *Statistical characteristics of film noise were theoretically explained and experimentally validated. This includes the Gaussianity of film noise, the radiation energy dependency and the collinearity of the NPS in relation to the OD signal.*
- *As a primary application, it was experimentally shown that the new digitisation procedure can replace traditional microdensitometer measurements. This includes the presentation of an original OD standard deviation correction procedure based on the deconvolution of the optical MTF.*
- *In a second application study, it was experimentally shown that the new procedure measures the film system unsharpness correctly.*

6.3 Industrial implementation and suggested future work

The work presented in this thesis is vital for computer simulations of radiographic testing such as performed in the nuclear industry e.g. at EDF and other industries. Therefore, the implementation of the presented models is currently being undertaken at the EDF R&D site in Paris-Saclay. This primarily includes the CHO Model Observer for automated image assessment of simulated radiographs as well as the noise model in its simplified form for application within industrial radiography. When this implementation is complete, the models emerged in this PhD project will be included in the EDF in-house simulation package MODERATO for radiographic inspections. The well-known and commercially available NDE simulation package CIVA [89] relies also on the MODERATO code as a source for its radiographic module [90]. Therefore, with time, the new models presented in this thesis will ultimately become available to the vast community using CIVA for industrial as well as academic purposes.

Furthermore, the French research organisation CEA (Atomic Energy and Alternative Energies Commission) is implementing the Model Observer presented in Chapter 3. The paper published by the author [7] aroused interest in the community, which followed the start of this second implementation project with the research group “Laboratoire de Mesures Nucléaires” at the CEA site in Cadarache, France.

A possible candidate for future investigations could be the incorporation of the Contrast Sensitivity Function (CSF) in the CHO Model Observer. It is known that the human visual system is particularly sensitive to specific spatial

frequencies [28], [29]. It could further improve the performance of the CHO if the images are pre-filtered according to the CSF.

Another future project could link the new noise model presented in this thesis with the CHO. The results generated with the CHO within this PhD project rely on the state-of-the-art noise model using white Gaussian noise. If the much more realistic experimentally-based noise model presented in this thesis is used for the CHO, it is expected that the results of the model observer should become even better and less scattered as the noise is then no longer overestimated. This is currently the case when using the state-of-the-art noise model.

Academic biography

Sebastian Eckel received the Bachelor of Science and Master of Science degrees in Mechanical Engineering from the Karlsruhe Institute of Technology (KIT), Germany, in 2013 and 2016 respectively. He holds also the Engineering Diploma (2016) and a Master Recherche degree in Mechanics of Materials (2015) from Arts et Métiers ParisTech, France.

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List of journal publications by the author

Eckel, S., Huthwaite, P., Zscherpel, U., Schumm, A., & Paul, N. (2019). Realistic Film Noise Generation Based on Experimental Noise Spectra. Accepted for publication by *IEEE Transactions on Image Processing*.

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Eckel, S., Huthwaite, P., Lowe, M., Schumm, A., & Guérin, P. (2018). Establishment and validation of the Channelized Hotelling Model Observer for image assessment in industrial radiography. *NDT & E International*, 98, 1-7.

Unrelated to the work presented in this thesis:

Eckel, S., Meraghni, F., Pomarède, P., & Declercq, N. F. (2017). Investigation of damage in composites using nondestructive nonlinear acoustic spectroscopy. *Experimental Mechanics*, 57(2), 207-217.

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