

Realistic Film Noise Generation Based on Experimental Noise Spectra

Sebastian Eckel, Peter Huthwaite, Uwe Zscherpel, Andreas Schumm, and Nicolas Paul

Abstract — Generating 2D noise with local, space-varying spectral characteristics is vital where random noise fields with spatially heterogeneous statistical properties are observed and need to be simulated. A realistic, non-stationary noise generator relying on experimental data is presented. That generator is desired in areas such as photography and radiography. For example, before performing actual X-ray imaging in practice, output images are simulated to assess and improve setups. For that purpose, realistic film noise modelling is crucial because noise downgrades the detectability of visual signals. The presented film noise synthesiser improves the realism and value of radiographic simulations significantly, allowing more realistic assessments of radiographic test setups. The method respects space-varying spectral characteristics and probability distributions, locally simulating noise with realistic granularity and contrast. The benefits of this approach are to respect the correlation between noise and image as well as internal correlation, the fast generation of any number of unique noise samples, the exploitation of real experimental data, and its statistical non-stationarity. The combination of these benefits is not available in existing work. Validation of the new technique was undertaken in the field of industrial radiography. While applied to that field here, the technique is general and can also be utilised in any other field where the generation of 2D noise with local, space-varying statistical properties is necessary.

Index Terms—Image quality, Noise simulation, Nondestructive testing, Radiography

I. 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 [1]: 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 [2], [3]. The human eye is not able to resolve single clusters of exposed silver particles, called grains, which typically vary between $0.2\ \mu\text{m}$ and $2\ \mu\text{m}$ [4], [5]. These grains agglomerate in random patterns, which are however resolvable and appear as graininess [4].

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. 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 [6]. 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 [1], [7], [8]. That granularity measure assumes a constant relationship between the standard deviation of Gaussian distributed film noise and the square root of the scanning aperture [9] specifying the resolution. However, the assumed constant relationship does not apply to aperture sizes below $10\ \mu\text{m}$ [3], [10]. In many applications, pixel sizes below $10\ \mu\text{m}$ are often necessary. This leads to an

S. Eckel is funded by the UK Engineering and Physical Sciences Research Council (EPSRC) ICASE number 15220134, with contributions from EDF S.A. R&D. P. Huthwaite is funded by an EPSRC Early Career Fellowship EP/M020207/1.

S. Eckel and P. Huthwaite are with the Department of Mechanical Engineering, Imperial College London, London, United Kingdom (e-mail: s.eckel16@imperial.ac.uk).

U. Zscherpel is with BAM Bundesanstalt für Materialforschung und -prüfung, Radiological Methods Division, Berlin, Germany.

A. Schumm and N. Paul are with EDF S.A., R&D Department, Paris, France.

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 [11], [12]. 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 [13] 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.

(3) Other approaches model the noise on the microscale as a grain distribution such as for example the Random Dot Models (RDM) [14]–[16]. 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 [6], [17]. 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 [18]. 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 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 paper 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 II, the new film noise generation method is presented in section III. 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 IV followed by the conclusion in section V, outlining the impact of the method on image simulation in industrial radiography.

II. 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 describe the concept of optical density.

A. 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 terms of harmonics. 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 [2], [3]. The spectrum contains information about the spatial frequencies of the noise and therefore stores data about spatial correlations or grain aggregations.

B. 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. This film blackening can be quantified by the concept of “vis-

ual diffuse Optical Density” (OD, see ISO 5, parts 1–3), which is a logarithmic ratio between the light falling upon and transmitting through the film. The optical density is defined as the negative logarithm of the transmittance T

$$OD = -\log_{10} T \quad (1)$$

and 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. The transmittance is defined by the ratio of the radiant flux transmitted through to that incident upon the surface. 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.

III. METHOD

The idea of the noise generation method introduced in this paper 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 paper is that the approach will be generalised to the non-stationary case, where the NPS varies locally as the underlying image signal changes. Afterwards, the new method and its implementation will be presented.

A. State-of-the-art

In the introduction, a noise generation method was briefly introduced that generates noise by filtering white noise with a specific NPS [18]. 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 [19]. This means that the NPS is the Fourier transform of the autocorrelation function of the noise [19]

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

with $\mathcal{F}_{2D}\{\}$ 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 with a filter h with frequency response $H = \mathcal{F}_{2D}\{h\} = \sqrt{NPS}$, leading to noise v

$$v = h * u = \mathcal{F}_{2D}^{-1}\{H \cdot U\} = \mathcal{F}_{2D}^{-1}\{\sqrt{NPS} \cdot U\} \quad (3)$$

where $*$ describes the convolution and U is the Fourier transform of u . 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 . That interpretation is of importance when describing the new method in section III.D.

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) 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

$$G(w) = \int_{-\infty}^w g(z) dz \quad (4)$$

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

$$w = F^{-1}(G(v)) \quad (5)$$

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 [20].

B. 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. 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 [21]. 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 (3) for the stationary case. In the spatial domain, this noise generation can be seen as a simple spatial filter

$$v = h * u. \quad (6)$$

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

$$v(\mathbf{x}) = h_{\mathbf{x}} * u \quad (7)$$

with

$$h_{\mathbf{x}} = \mathcal{F}_{2D}^{-1}\{\sqrt{NPS_{\mathbf{x}}}\}. \quad (8)$$

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

$$v(\mathbf{x}) = \mathcal{F}_{2D}^{-1}\{\sqrt{NPS_{\mathbf{x}}} \cdot \mathcal{F}_{2D}\{u\}\}(\mathbf{x}) \quad (9)$$

and, as mentioned in section III.A, the noise Fourier transform operation $\mathcal{F}_{2D}\{u\}$ 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

$$w(\mathbf{x}) = F_{\mathbf{x}}^{-1}(G_{\mathbf{x}}(v(\mathbf{x}))) \quad (10)$$

and the resulting noise is non-stationary with local statistical properties. An example result of that method is shown in Fig. 1.

C. 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 pos-

sible in practice, because only NPS data for a limited, discrete number of signals, can be measured. A method to simulate

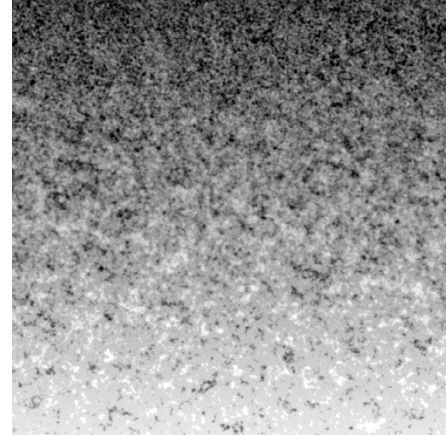


Fig. 1. Example result of non-stationary noise with locally varying spectral properties

NPS data for any signal case is also presented in this section.

The approach to establishing 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 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 [19].

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 I . To derive the spectral properties of the noise in this specific signal case, the NPS of the noise is given by

$$NPS = \lim_{X,Y \rightarrow \infty} \left\langle \frac{|\mathcal{F}_{2D}(I)|^2}{(X \cdot Y)^2} \right\rangle \quad (11)$$

where $\mathcal{F}_{2D}$ represents the Fourier transform in 2D, X, Y are the dimensions of the noise image I 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. Averaging the NPS over n sub images leads to a better estimation for the NPS, known as the Welch's method [22], [23]. 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

$$NPS = \frac{1}{n} \sum_{i=1}^n \frac{|\text{FFT}(I_i)|^2}{(p_x \cdot p_y)^2} \quad (12)$$

where NPS_{2D} is the averaged and normalised NPS of the noise image in 2D, n is the number of sub images, I_i is the i -th sub-image and $p_{x,y}$ is the dimension in number of pixel 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.

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 Fig. 2.

D. 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 Fig. 1 was generated by segmenting the input image in 20 areas. A straightforward approach is to seg-

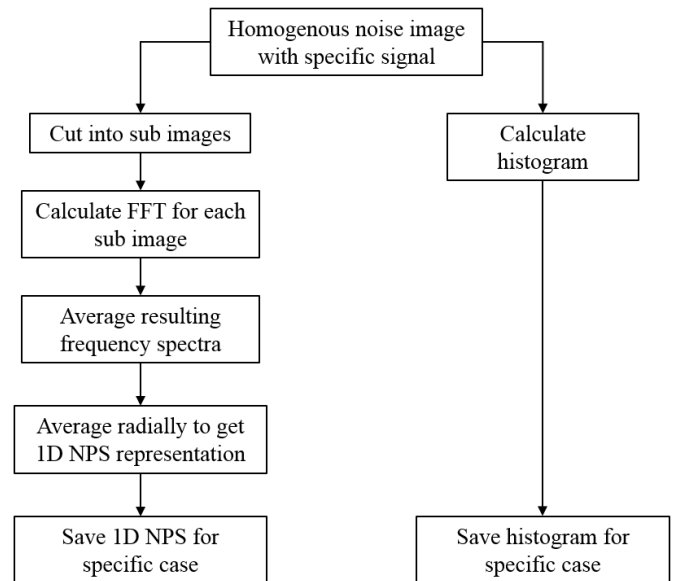


Fig. 2. Flowchart of the approach to build up an experimental database; the process is repeated for any available homogenous noise image of the database

ment 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

$$NPS_\rho := (1 - \rho)NPS_0 + \rho NPS_1 \quad (13)$$

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

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 [24]. 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 [25]. It can be noted that the state-of-the-art method filters white Gaussian noise, which is also similar to randomising the phase [26].

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 single artificial phase ma-

trix 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 (7), where only one and the same Gaussian noise u 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 [24] 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 [27]. The function computes a grayscale transformation function H , which minimises the difference between the cumulative histogram (cumulative distribution function) c_0 of the image to be processed and the cumulative target histogram c_1 for all pixel intensities k

$$\min |c_1(H(k)) - c_0(k)|. \quad (14)$$

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

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 noiseless input image I_{input} to receive the noisy input image $\tilde{I}$

$$\tilde{I} = I_{input} + w. \quad (15)$$

The method for generating a non-stationary noise image is also summarised in Fig. 3 and an application result is presented in Fig. 1.

E. Simplified method for simulating statistically non-stationary noise

In some scenarios (for example with film noise), it may be possible to simplify the general method described above. 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 [19]

$$\sigma^2 = \iint NPS du dv \quad (16)$$

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

$$NPS_{target} := \left(\frac{\sigma_{target}}{\sigma_{basis}} \right)^2 \cdot NPS_{basis} \quad (17)$$

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 [28]. 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.

IV. 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 is described for the case of film noise simulation in industrial radiography. Realistic image simulation is of high interest for industrial radiography in Non-Destructive Evaluation (NDE). NDE is a term that combines all examination methods used to investigate the structural integrity of a component without causing any permanent change to the structure. The objective of applying an NDE method is to detect internal structural defects such as cracks, inclusions or internal voids.

Radiography is a widely used 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 [29]. These simulated images are afterwards assessed for the purpose of indirect, computer based test setup improvements or testing procedure qualification [30]. 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 [31] in real X-ray images and must be simulated too.

In section IV.A, the characteristics of film noise are presented, allowing the assumptions necessary for the application of the simplified method presented in section III.E to be made. Afterwards, section IV.B 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 [32]. Nevertheless, an image feature extraction method established in the area of texture analysis basing on co-occurrence matrices [33] 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 IV.C respectively in section IV.D.

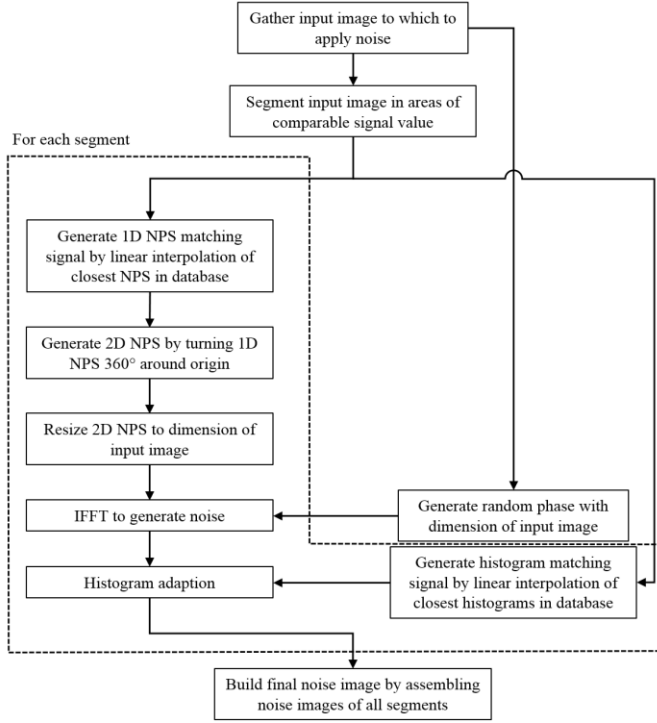


Fig. 3. Complete process for generation of non-stationary noise

A. 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 [19].

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 [34]. The characteristic of the Poisson distribution is that its variance is equal to the expected number of quanta. The so called Nutting formula [15], [19] describes how the OD is proportional to the number of exposed particles in the film emulsion

$$OD = 0.434 \frac{n_A \bar{a}}{A} \quad (18)$$

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

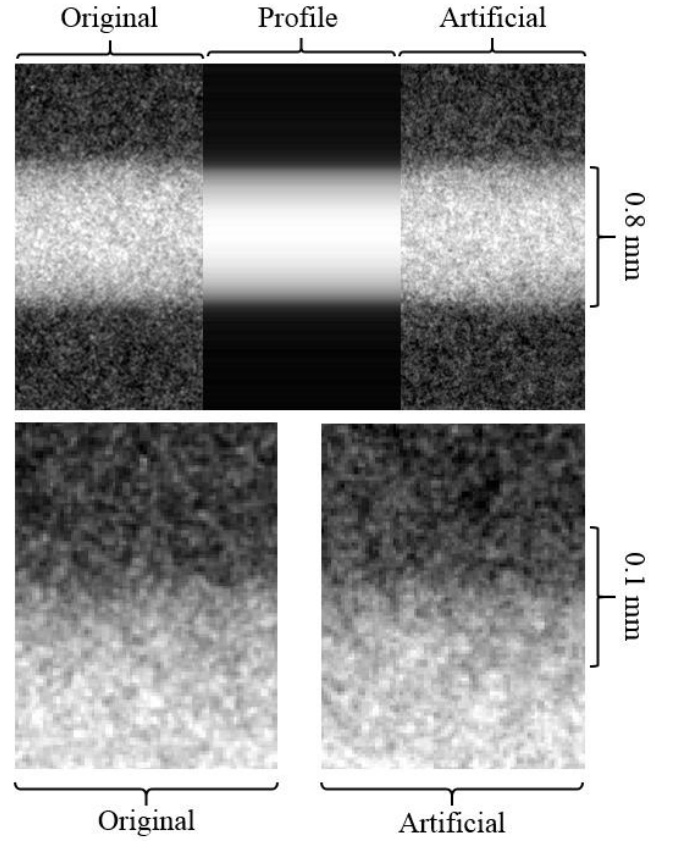


Fig. 4. Comparison of original noise (top left), profile (top centre) and artificial noise (top right) with 8 x zoomed details of original noise (bottom left) and artificial noise (bottom right)

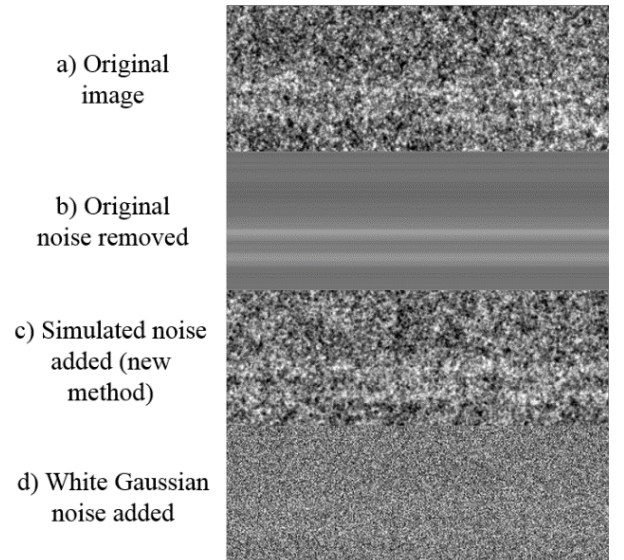


Fig. 5. Original image of duplex wire IQI pair D11 (a), IQI wire pair profile extracted (b), noise generated by the new method added to the profile (c), white Gaussian noise added to the profile (d); IQI wire pair diameter: 0.08 mm each

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 [19].

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 [28] has verified that the distribution of the original noise images is practically Gaussian distributed. 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 [28] 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.

B. 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 [28] to investigate AGFA STRUCTURIX films of three different film system classes C1, C3 and C5 in accordance to [7]. 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 optical density 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 [28].

C. 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 [35], 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). A first example is shown in Fig. 4.

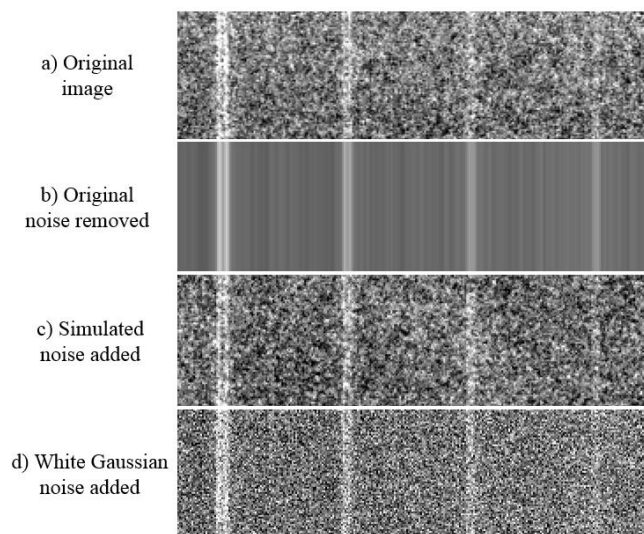


Fig. 6. Original image of duplex wire IQI D10 to D13 taken by a laser scanner (a), IQI profile extracted (b), noise generated by the new method added to the profile (c), white Gaussian noise added to the profile (d)

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 paper is incorporated into the clean image to test the performance. Visually the characteristics of the noise are indistinguishable. This is reinforced with the zoomed images on the bottom row of the figure.

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. Fig. 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 $6.662 \mu\text{m}$. 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 [36], the resulting image looks much different as shown in part d).

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. Four wire pairs of the IQI according to ISO 19232-5 of different diameters are shown in part a) of Fig. 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 Fig. 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 Fig. 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 undistinguishable from the original image. These comparisons prove visually the effectiveness of the noise generation method based on phase randomisation.

D. 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 [37]. 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 [38]. 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

$$GLCM_{\Delta x, \Delta y}(i, j) = \sum_{x, y} \begin{cases} 1, & \text{if } B(x, y) = i \text{ and } B(x + \Delta x, y + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \quad (19)$$

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.

Image features can be extracted by calculating statistical measures from the GLMC, such as contrast, correlation, ener-

gy or homogeneity. These statistical measures have been defined in [33] and they are interrelated and have redundancies [39]. This paper focuses in comparing the statistical property of contrast. The contrast C is defined as

$$C_{\Delta x, \Delta y} = \sum_{i, j} |i - j|^2 GLCM_{\Delta x, \Delta y}(i, j) \quad (20)$$

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 x 500 pixels was investigated. The GLCM of original and artificial noise are investigated by visualising them in Fig. 7. To facilitate the interpretation, the grey level range of the noise images was downscaled/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. Fig. 8 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 (these are not presented here for brevity). Hence, it can be stated that noise generated by the presented method is statistically not distinguishable from original noise.

V. CONCLUSIONS

A new, non-stationary film noise simulation method was presented 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

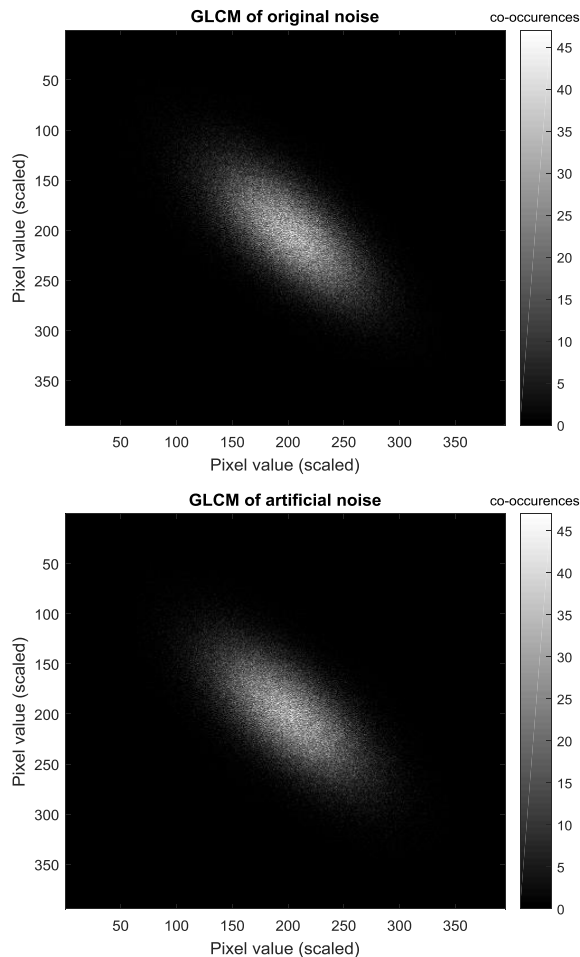


Fig. 7. GLCM of original and artificial noise whereas the image grey levels are downscaled by factor 10

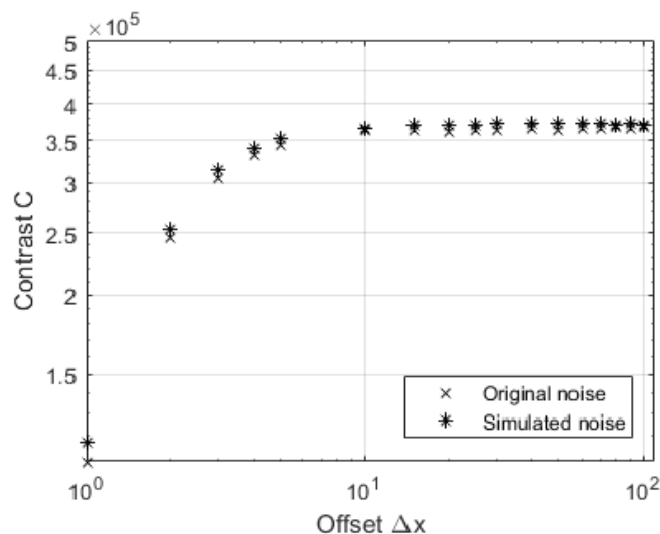


Fig. 8. GLCM contrast feature of original and simulated noise for various offsets Δx

the application of the simplified version of the noise generation method for film 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. 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.

ACKNOWLEDGEMENT

The authors thank Dr Sebastian Heinlein (Imperial College London) for helpful discussions. The authors would also like to thank Ms Céline Paré (EDF S.A. and UPMC – Paris 6) and Mr Hao Zhou (BAM Berlin and Tsinghua University Beijing) for having carried out microscopic investigations.

REFERENCES

- [1] J. Geigel and F. K. Musgrave, "A model for simulating the photographic development process on digital images," in *Proceedings of the 24th annual conference on Computer graphics and interactive techniques - SIGGRAPH '97*, 1997, pp. 135–142.
- [2] R. C. Jones, "New method of describing and measuring the granularity of photographic materials," *J. Opt. Soc. Am.*, vol. 45, no. 10, pp. 799–808, 1955.
- [3] K. Hacking, "Photographic film grain: a study with the aid of an optical correlator," The British Broadcasting Corporation – Engineering Division, UK, 1963.
- [4] C. Gomila, J. Llach, and J. A. Cooper, "Film grain simulation method," U.S. Patent 2006/0082649 A1, 2006.
- [5] C. Paré and R. Jonchière, "Amélioration de la modélisation de la granularité du film dans le code de simulation radiographique MODERATO," EDF R&D Internal Report, unpublished, Paris, France, 2017.
- [6] A. Newson, J. Delon, and B. Galerne, "A Stochastic Film Grain Model for Resolution-Independent Rendering," *Comput. Graph. Forum*, vol. 36, no. 8, pp. 684–699, 2017.
- [7] International Organization for Standardization, "Non-destructive

- testing — Industrial radiographic film Part 1: Classification of film systems for industrial radiography (ISO 11699-1:2008),” ISO 11699-1:2011, 2011.
- [8] A. Schumm and U. Zscherpel, “La modélisation d’un film radiographique selon la norme européenne EN584 - Radiographic film modelling according to EN584,” *COFREND - Congrès Toulouse 2008*, 2008. [Online]. Available: <http://www.ndt.net/article/cofrend2008/papers/128.pdf>.
- [9] E. W. H. Selwyn, “Experiments on the Nature of Graininess,” *Photogr. J.*, vol. 79, pp. 513–524, 1939.
- [10] G. C. Higgins and K. F. Stultz, “Experimental Study of rms Granularity as a Function of Scanning-Spot Size,” *J. Opt. Soc. Am.*, vol. 49, no. 9, pp. 925–929, 1959.
- [11] D. T. Kuan, A. A. Sawchuk, T. C. Strand, and P. Chavel, “Adaptive Noise Smoothing Filter for Images with Signal-Dependent Noise,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-7, no. 2, pp. 165–177, 1985.
- [12] O. K. Al-Shaykh and R. M. Mersereau, “Restoration of lossy compressed noisy images,” *IEEE Trans. Image Process.*, vol. 8, no. 10, pp. 1348–1360, 1999.
- [13] C. Gomila and A. Kobilansky, “SEI message for film grain encoding,” *Joint Video Team (JVT) of ISO/IEC MPEG & ITU-T VCEG 8th Meeting, Geneva, CH, 23-27 May, 2003*, 2003. [Online]. Available: http://wftp3.itu.int/av-arch/jvt-site/2003_05_Geneva/JVT-H022.zip.
- [14] M. Savelli, “Theoretical and experimental study of the granularity of uniformly exposed photographic films,” *Rev. Opt. Theor. Instrum.*, vol. 38, pp. 269–281, 1959.
- [15] P. G. Nutting, “On the absorption of light in heterogeneous media,” *Philos. Mag. Ser. 6*, vol. 26, no. 153, pp. 423–426, 1913.
- [16] K. Tanaka and S. Uchida, “Extended random-dot model,” *J. Opt. Soc. Am.*, vol. 73, no. 10, pp. 1312–1319, 1983.
- [17] A. Newson, N. Faraj, J. Delon, and B. Galerne, “Realistic Film Grain Rendering,” *Image Process. Line*, vol. 7, pp. 165–183, 2017.
- [18] I. Stephenson and A. Saunders, “Simulating Film Grain using the Noise-Power Spectrum,” in *Theory and Practice of Computer Graphics*, I. S. Lim and D. Duce, Eds. The Eurographics Association, 2007, pp. 69–72.
- [19] J. C. Dainty and R. Shaw, *Image Science: Principles, Analysis and Evaluation of Photographic-type Imaging Processes*. Academic Press, 1974.
- [20] B. Galerne, A. Leclaire, and J. Rabin, “A Texture Synthesis Model Based on Semi-Discrete Optimal Transport in Patch,” *SIAM J. Imaging Sci.*, vol. 11, no. 4, pp. 2456–2493, 2018.
- [21] S. Eckel, P. Huthwaite, and A. Schumm, “Automating defect visibility assessment in radiographs and sophisticated film noise modelling,” in *12th European Conference on Non-Destructive Testing*, 2018.
- [22] P. D. Welch, “The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms,” *IEEE Trans. audio Electroacoust.*, vol. 15, no. 2, pp. 70–73, 1967.
- [23] G. Gilet, B. Sauvage, K. Vanhoey, J.-M. Dischler, and D. Ghazanfarpour, “Local Random-Phase Noise for Procedural Texturing,” *ACM Trans. Graph.*, vol. 33, no. 6, p. 195, 2014.
- [24] B. Galerne, Y. Gousseau, and J. Morel, “Random Phase Textures : Theory and Synthesis,” *IEEE Trans. Image Process.*, vol. 20, no. 1, pp. 257–267, 2011.
- [25] J.-P. Lewis, “Texture Synthesis for Digital Painting,” in *SIGGRAPH ’84 Proceedings of the 11th annual conference on Computer graphics and interactive techniques*, 1984, vol. 18, no. 3, pp. 245–252.
- [26] D. Nerini, N. Besic, I. Sideris, U. Germann, and L. Foresti, “A non-stationary stochastic ensemble generator for radar rainfall fields based on the short-space Fourier transform,” *Hydrol. Earth Syst. Sci.*, vol. 21, pp. 2777–2797, 2017.
- [27] MathWorks, “histeq – Enhance contrast using histogram equalization,” 2017. [Online]. Available: <https://de.mathworks.com/help/images/ref/histeq.html>.
- [28] S. Eckel, U. Zscherpel, P. Huthwaite, N. Paul, and A. Schumm, “Radiographic film system classification and noise characterisation by a new camera based digitisation procedure,” *Submitt. to NDT E Int.*, 2019.
- [29] A. Bonin, B. Lavayssière, and B. Chalmond, “Moderato: A Monte-Carlo radiographic simulation,” in *AIP Conference Proceedings*, 2000, vol. 509, no. 1.
- [30] S. Eckel, P. Huthwaite, M. Lowe, A. Schumm, and P. Guérin, “Establishment and Validation of the Channelized Hotelling Model Observer for Image Assessment in Industrial Radiography,” *NDT E Int.*, vol. 98, pp. 1–7, 2018.
- [31] K. Doi, “Basic Imaging Properties of Radiographic Systems and Their Measurement,” in *Progress in Medical Radiation Physics*, C. G. Orton, Ed. Boston, MA: Springer US, 1985, pp. 181–248.
- [32] B. T. Oh, S. M. Lei, and C. C. J. Kuo, “Advanced film grain noise extraction and synthesis for high-definition video coding,” *IEEE Trans. Circuits Syst. Video Technol.*, vol. 19, no. 12, pp. 1717–1729, 2009.
- [33] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural Features for Image Classification,” *IEEE Trans. Syst. Man. Cybern.*, vol. SMC-3, no. 6, pp. 610–621, 1973.
- [34] U. Zscherpel and U. Ewert, “Industrial Radiography,” in *Handbook of X-ray Imaging: Physics and Technology*, P. Russo, Ed. CRC Press, 2017, pp. 595–617.
- [35] D. Hepper, “Investigating properties of film grain noise for film grain management,” in *Proceedings 2013 IEEE 3rd International Conference on Consumer Electronics - Berlin, ICCE-Berlin 2013*, 2013, no. 3, pp. 185–188.
- [36] P. Guérin, “Validation de la prise en compte de la granularité des films dans MODERATO,” EDF R&D Internal Report, unpublished, Paris, France, 2015.
- [37] G. N. Srinivasan and G. Shobha, “Statistical Texture Analysis,” *Proc. world Acad. Sci. Eng. Technol.*, vol. 36, no. December, pp. 1264–1269, 2008.
- [38] J. Dai, O. C. Au, C. Pang, W. Yang, and F. Zou, “Film grain noise removal and synthesis in video coding,” *ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc.*, pp. 890–893, 2010.
- [39] F. Tominta and S. Tsuji, *Computer Analysis of Visual Textures*. Kluwer Academics Publishers, 1990.

Sebastian Eckel received the B.Sc. and M.Sc. 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.

Since 2016, he is pursuing the PhD degree with the Non-Destructive Testing group in the Mechanical Engineering Department at Imperial College, London, UK, in collaboration with EDF SA, Paris, France.

Mr Eckel is granted with an Industrial CASE award from the Engineering and Physical Sciences Research Council (EPSRC), UK.

Peter Huthwaite is a Senior Lecturer in Mechanical Engineering at Imperial College London, UK, and holds MEng and PhD degrees from Imperial in mechanical engineering. He leads imaging research within the Non-Destructive Testing group, and has undertaken extensive work on improving imaging algorithms, particularly for guided wave tomography.

His main research area is limited data imaging for ultrasonics and radiography, to reduce issues associated with acquisition time, system complexity and physical restrictions which occur in practice. His interests include the development of quantitative image reconstruction algorithms, with applications in medicine for breast cancer diagnosis and NDT for early stage damage detection. He also has interests in the numerical modelling of waves, and has developed the GPU-based finite element software package Pogo.

Uwe Zscherpel received the Diploma (1987) and the PhD (1993) in experimental physics from the University of Leipzig, Germany.

From 1990 to 1992, he was a Research Associate at the Central Institute of Physical Chemistry at the Academy of Sciences of the German Democratic Republic in Berlin, Germany. In 1992 he changed to the Federal Institute for Materials Research and Testing (BAM) in Berlin, Germany, and has been a Project Leader and since 2009 head of the working group “Digital Radiology and Image Analysis” in the field of non-destructive testing. Today he heads an accredited testing laboratory for international NDT film certification and digital film replacement. He is member of various standardisation committees at DIN, CEN, ISO, IEC and ASTM for industrial applications of radiological imaging methods.

Andreas Schumm holds a Diploma in electrical engineering and a PhD from the Technical University of Berlin, Germany.

He is a Project Manager at EDF R&D in Paris, France, and he worked at the Federal Institute for Materials Research and Testing (BAM) in Berlin, Germany, before joining EDF R&D in 1995. His principal research area is computer modelling of non-destructive testing methods, in particular for radiography and ultrasound.

Nicolas Paul received the Engineering Diploma from Supélec, France, in 1999 with a major in signal processing and the PhD degree in machine learning from CNAM, France, in 2008.

He joined EDF R&D, Paris, France, in 2009 where he mainly works on signal, image and video processing applied to nuclear safety.

Dr Paul is inventor or co-inventor of several patents in these fields, including video restoration in high turbulence context (SFEN innovation price 2015, EDF Pulse laureate 2014), clogging rate estimation in steam generator and ultrasound processing in case of high structural noise.