Optimization of Acquisition Parameters for Radiography using Numerical Simulation

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Abstract. X-ray imaging is a powerful tool for the inspection of industrial castings. The radiograph quality is highly dependant of a large number of inspection parameters: generator settings, object geometrical parameters and detector characteristics. When trying to optimize these parameters, the large dimensionality of the problem makes the manual investigation of the solution difficult.
Within European project VERDICT, we propose to use simulation to predict the optimal imaging conditions, and thus to help the operator to tune the system prior to the inspection. We use a simulation software tool Sindbad. For every particular set of acquisition parameters, a corresponding radiograph is simulated. A main loop scans the whole parameters space to find the optimal parameters set, using a defect detectability criteria as cost function. Detector response is precisely modelled, both for film and flat panel. Different versions of the detectability criteria are discussed, depending on whether detection is performed by numerical processing or human inspection. Experimental validation of our approach is performed using components from aeronautics.

1. Introduction

To inspect industrial castings, X-ray imaging is a powerful tool giving information on the sample internal structures. The inspection goal is usually to detect and classify the defects produced by the manufacturing process. The radiograph quality, which is essential for this goal, is highly dependant of a large number of inspection parameters: generator settings (tube voltage, current and exposure), object geometrical parameters (orientation, distance to the source) and detector characteristics, different from film to digital detector. When trying to optimize these parameters, the large dimensionality of the problem makes the manual investigation of the solution difficult. Furthermore it should be processed for every new sample or inspection task. For these reasons, an automatic tool would be very helpful for the user to determine the optimal acquisition parameters set.
Such a tool requires modeling to predict the quality of the radiograph that would be produced with a particular set of acquisition parameters. Some authors have proposed to model mathematically the relationship between the system parameters and indicators of image quality [1]. If these types of models can be easily defined in the simplified perfect case, they become complex and finally unusable when integrating all the physical phenomena and various disturbances that may occur in the X-ray attenuation and measurement process. Another approach is based on the use of a software module allowing to simulate numerical radiographs, image quality indicators being then measured on this image thanks to image processing algorithms [2]. The simulation module should be able to produce realistic radiographs, taking into account phenomena as backscattering radiation, focal blurring, and should provide accurate and validated model of detectors.

Within the European project VERDICT, we have developed an automatic tool based on a simulation software module implemented by our laboratory, Sindbad [3, 4]. Image quality is quantified by a defect detectability criteria. A global optimization loop allows to determine the optimal parameters set. In this paper we present the method – detailed in [5].

2. The proposed approach

2.1 An optimization loop based on simulation

The global approach that we propose is presented in Figure 1. We describe the acquisition radiographic system, and the component to be inspected using CAD model. Representative defects are inserted numerically in the object model. For every set of system parameters, we assume that a defect detectability criteria (*DDC*) can be computed, based on image processing algorithms for defect detection – it will be detailed in §3. This criteria allows to quantify radiograph quality in terms of inspection requirements, and thus the interest of a given parameters set. A global loop scans the whole parameters space to find the optimal parameters set. Several detector models are available: conventional film, scintillator screen optically coupled to CCD camera, and flat panel. To deal with complex casts and particularly defects insertion, new functionalities have been added to Sindbad [6].

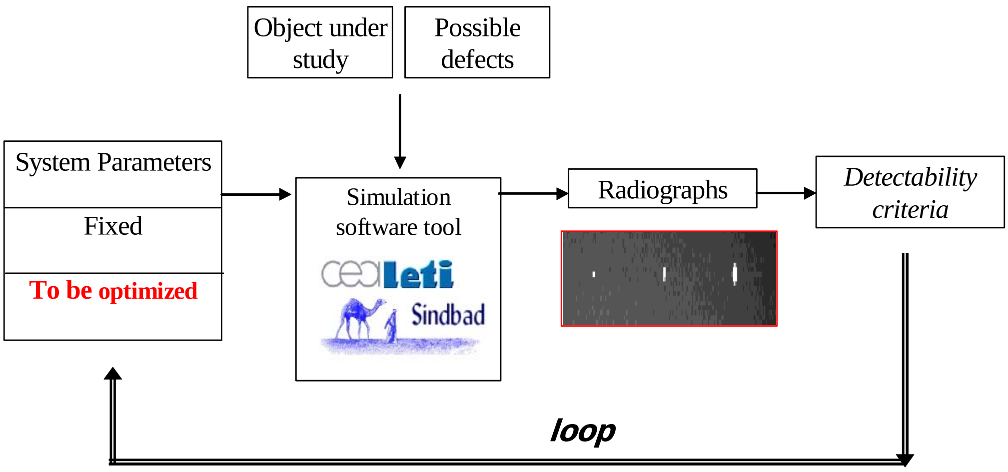

Figure 1: Global scheme of the optimization approach.

2.2 The parameters to be optimized

Once the acquisition system has been chosen (source and detector), the parameters that can be tuned for acquisition are typically those given by the underneath table. Other geometrical parameters can be added, specifically to the considered application.

name	*meaning*	*Constraints*
KV	High voltage of the source	Device constraints
mAs	Intensity x acquisition_time	System & acquisition constraints
D_{SD}	Distance source detector	Mechan. constraints
D_{SO}	Distance source object	Mechan.constraints + defect visible
T	Translation	Mechan. constraints + defect visible
R	Rotation	defect visible

2.3 The optimization algorithm

Different approaches can be considered for the optimization loop. The first one consists in an exhaustive scanning of the set of parameters - quantifying all the possible combinations. More efficient methods can be envisaged. The simplex algorithm is well known, but requires an initial solution not too far from the optimum. More sophisticated methods as simulated annealing optimization have already been used successfully, in a context similar to ours [2]. Notice that these methods usually assume some regularity property of the optimization surface, which is not necessarily true in case of a non-convex criteria or if constraints exist on some parameters.

Finally we choose the exhaustive scanning solution, as the low number of parameters assures a reasonable execution time. It is applied within a multi-resolution scheme: once the search space has been made discrete (choice of incremental step for each parameter), a first optimum is determined using a rough step and then refined locally with a finer step.

Radiographs simulation taking into account scattering radiation is time consuming. Thus we propose to find the optimum using radiographs without scattering simulation, and then to refine locally the optimum using radiographs including scattering. This approach relies on the assumption that scattering effect does not modify the optimum too much. We have validated experimentally on the tested components the fact that the addition of scatter effect induces a slight shift of the optimization surface.

3. Defect Detectability Criteria

3.1 Contrast-to-Noise Ratio (CNR)

Contrast-to-noise Ratio (*CNR)* is one of the most frequent parameters used in digital radiography to quantify the capability of a system to achieve an inspection task. For instance [7] expresses standard based requirements in terms of *CNR* and spatial resolution. Notice that *CNR* corresponds to Signal-to-Noise Ratio (*SNR*) after flattening the local background around the defect. It is defined by: $CNR = C/\sigma$ where the contrast is given by the difference of the distribution expectation inside the defect and in the background, $C = |E_D - E_B|$, and σ the variance of the two distributions, supposed to be similar. This assumes that defect size is sufficient to allow robust estimation of expectation, which is not true for defects of a few pixels size. If we consider a perfect system (monochromatic source, perfect detector response, no scattering radiation) we can write the *CNR* for a lack-of-material defect as a function of some system parameters. Let us note N_0 the emitted photons number, N the absorbed photons number, μ the material attenuation coefficient, L its length, and th_{def} the defect thickness. The defect contrast on the attenuation image is given by $C = \mu \cdot th_{\mathrm{def}}$ and the estimated noise on attenuation measurement is: $\sigma(att) = 1/\sqrt{N} = e^{\mu \cdot L}/\sqrt{N_0}$. Consequently we get: $CNR = \sqrt{N_0} \cdot e^{\mu(E) \cdot L} \cdot \mu(E) \cdot th_{def}$. Notice that N_0 depends on *KV*, *mAs*, D_{SD}, the term ($e^{\mu(E) \cdot L} \cdot \mu(E)$) depends on *E*, thus on *KV*, and the geometry is addressed by th_{def} and *L*. This model is too simplified to be applicable in true conditions, thus we propose another estimation of *CNR*.

3.2 Computation of CNR using image processing

Within VERDICT, we use simulated radiographs to estimate the *CNR*. We consider a realistic radiographic system (polychromatic source, non perfect detector response...) and noise simulation. This allows a correct estimation of the defect contrast, local noise, thus *CNR*. More precisely we simulate radiographs of the component without the defect (background) and with the defect, both in noisy and noise-free version for the one containing the defect. By subtracting the background to the two others images, we get flatten images of the defect, with and without noise. An example is given in Figure 2.

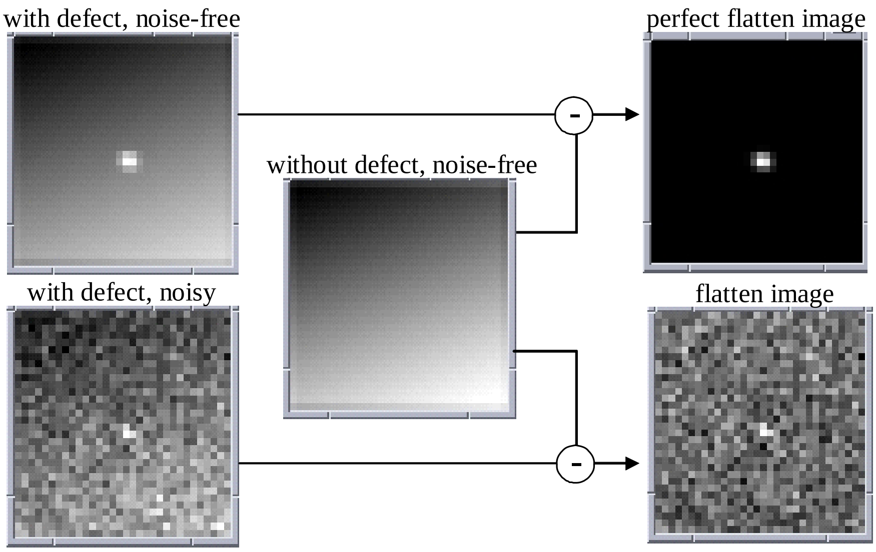

Figure 2: example of flattening process applied on noisy and noise-free images.

Then we perform, using usual image processing algorithms:

- defect detection, estimation of defect contrast, size, location on flatten noise-free image
- local noise estimation on flatten noisy image,
- dose estimation on noise-free image – in case of film.

From that we deduce the *CNR* of the defect. This approach is summarized in Figure 3.

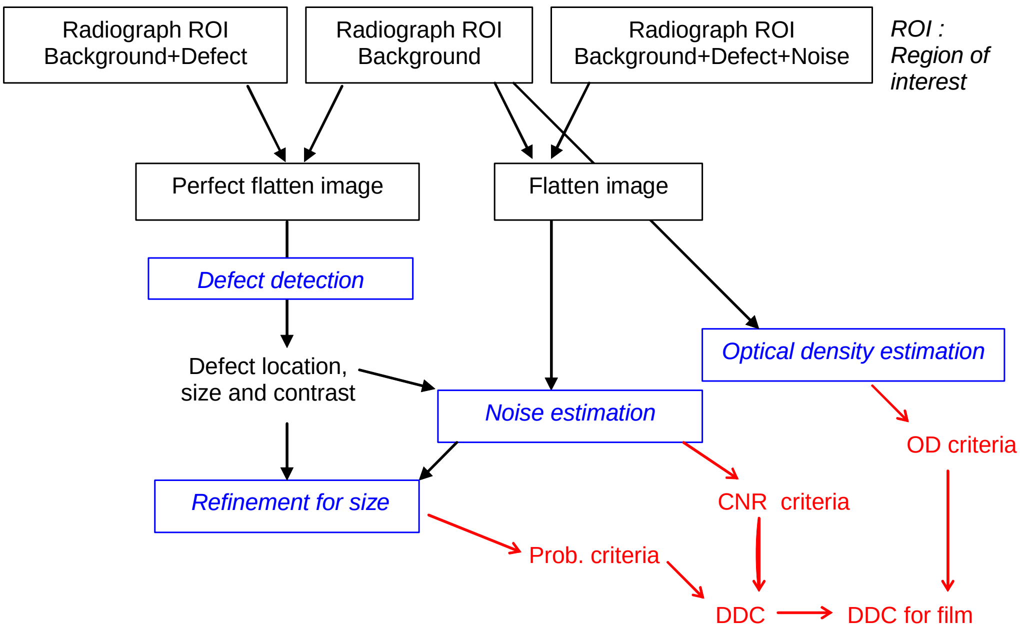

Figure 3: scheme for computing defect detectabiliy criteria (*DDC*).

This *CNR* criteria does not take into account the defect size. Nevertheless this influence is well known in image processing. It is clear that it is easier to detect a 10 pixels defect than a

2 pixels one, even with the same *CNR*. Consequently we propose to define the *DDC* by weighting the *CNR* by a size function: $DDC = CNR \cdot f(size)$ where *size* is the defect size in the detector plane. *f(size)* is a function that is monotonic but constant from a size of about 10 pixels, for instance $f(size) = 1-(1-p)^{size}$ where p can be interpreted with a probabilistic meaning, and related to C/σ.
In case of film radiography, to take into account the usable dynamic range of the film, we propose an additional weight, function of the contrast of the defect expressed in optical density. This weighting function can be a gate, typically $[2,4]$ or a smoother one, depending on the optical density function. Saturation effects have also been considered in case of film.

3.3 Visual criteria for human inspection

The *DDC* criteria proposed above is well–adapted to automatic processing of radiographs acquired by digital detectors (IIR or flat panel). But when these radiographs are analyzed by a human operator via a visual screen or from radiographic film, it is no more convenient, as illustrated by the following example, presenting a radiographic inspection of a stiffener part. Figure 4 presents zooms on noise-free background, noisy radiograph to be inspected, and subtraction. Defect is clearly more visible on the right image than on the middle one. This is due to the background, especially its "slope" in the defect area.

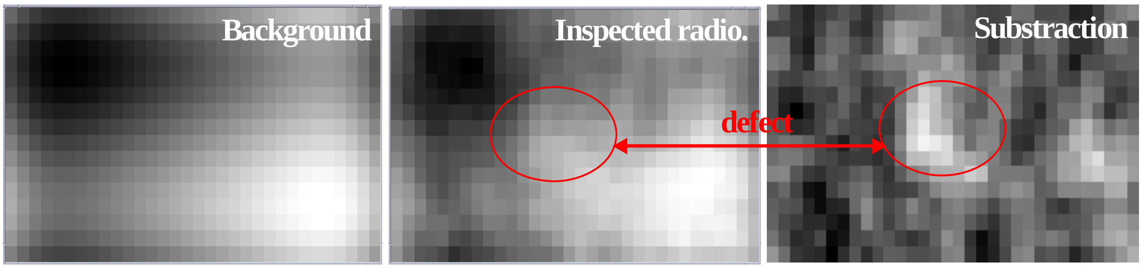

Figure 4: defect visibility on the inspected radiograph and the flatten one get by subtraction.

Consequently we propose an additional criteria, based on a "contrast-to-slope" ratio, which is the ratio of the contrast of the defect to local slope. This slope, or gradient, is normalized by the 2D defect size. We get: $CSR = \dfrac{Contrast}{slope \cdot \sqrt{size}}$. The slope is estimated by local plane approximation of the radiograph levels in the defect area. It may be disturbed by structures. Thus we perform a critical analysis of the defect neighborhood. The defect mask being previously determined during defect detection step, we apply a dilatation of this mask, conditionally to the present structures, and slope estimation is done inside this window. Considering the example of Figure 4, we get a *DDC* criteria of 5.2, meaning that the defect is theoretically detectable, but the *CSR* is very low (0.36), allowing to conclude that it is not detectable by a human inspection.
CSR is an additional criteria devoted to the case of human visual inspection, but not sufficient to status on detectability, because it does not take into account the presence of noise. For decision, it has to be used associated with DDC, eventually in a combined way.

4. Implementation and validation

4.1 Software implementation

The software OPTIM3D has been written within the framework of Sindbad. The implementation has been optimized, especially to speed up the program by avoiding computing redundant data, in both analytical and Monte Carlo mode. The computing time for each configuration is reduced by recovering information from previous ones, for instance restricted search window for similar geometrical configuration.

Using analytical mode, the optimization process spends several hours (between 3 and 12) for about 1000 or 2000 different configurations, depending on the complexity of the object and on the size of the defect. When considering scatter radiation, the optimization is slower. To speed it up, the optimization algorithm is adapted. The idea is to recover scattered images computed for specific intensity of source and to use it to deduce scattered images for different intensity but same geometry and voltage, just by applying a multiplying factor. Furthermore, the scattered image is estimated only with the object without defect. Indeed, we can reasonably admit that the presence of the defect in the object does not affect the scattered radiation. The computational time of Monte Carlo simulations depends mainly on the number of emitted photons, and on object attenuation.

4.2 Experiments

We present now the example of a stiffener part from SNECMA (Figure 5). The defect is a crack, described in a CAD file. Its dimensions are approximately 1 x 0.2 x 0.2 mm^3.

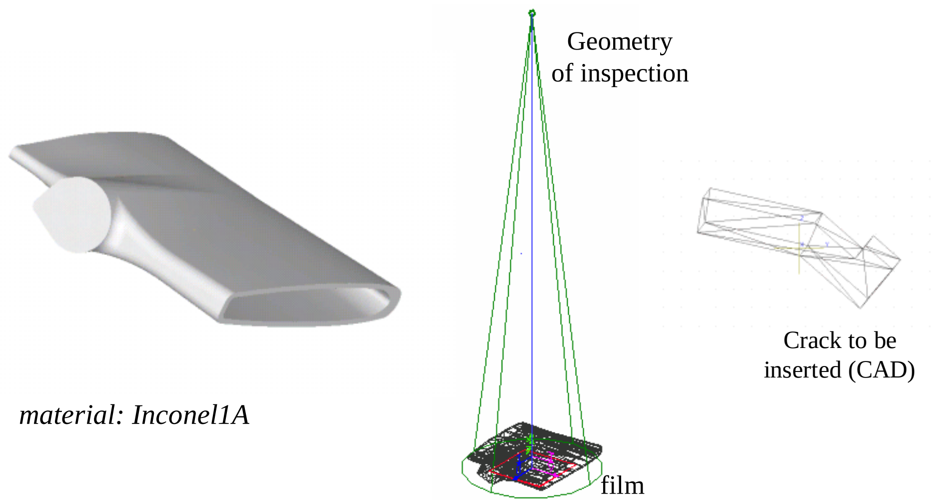

Figure 5: Radiographic inspection of the SNECMA stiffener part.

We use a specific sensitometry curve obtained previously thanks to experimental calibration. Pixel size of modelling is taken equal to the pixel size after digitalisation of the film, that is to say 315 microns, and grain size is 1.5 microns.

Here is the description of the optimization loop performed in the case of film inspection:

	Minimum	*Maximum*	*Inc. step*	*Finer step*	*Typical value used*	*Remark*
KV high voltage	100 kV	160 kV	10	5 or 2	130	
mAs flux	800	2400	0mA/20s	0mA/5s	1600	I = 20 mA T = 40 to 120s
D_{SO} source-object	400	915	50	20	650	
D_{SD} source-film	$D_{SD} = D_{SO}$ + 15 mm NOT VARYING					

The optimization consisted in a loop of 900 SINDBAD simulations, in analytical mode. Calculation time was approximately 3h. Figure 6 presents the values of the *DDC* criteria, according to 3 variables: voltage, distance source-object and dose parameter (mAs). A surface is drawn for each value of dose (800, 1200, 1600, 2000, 2400 mAs).

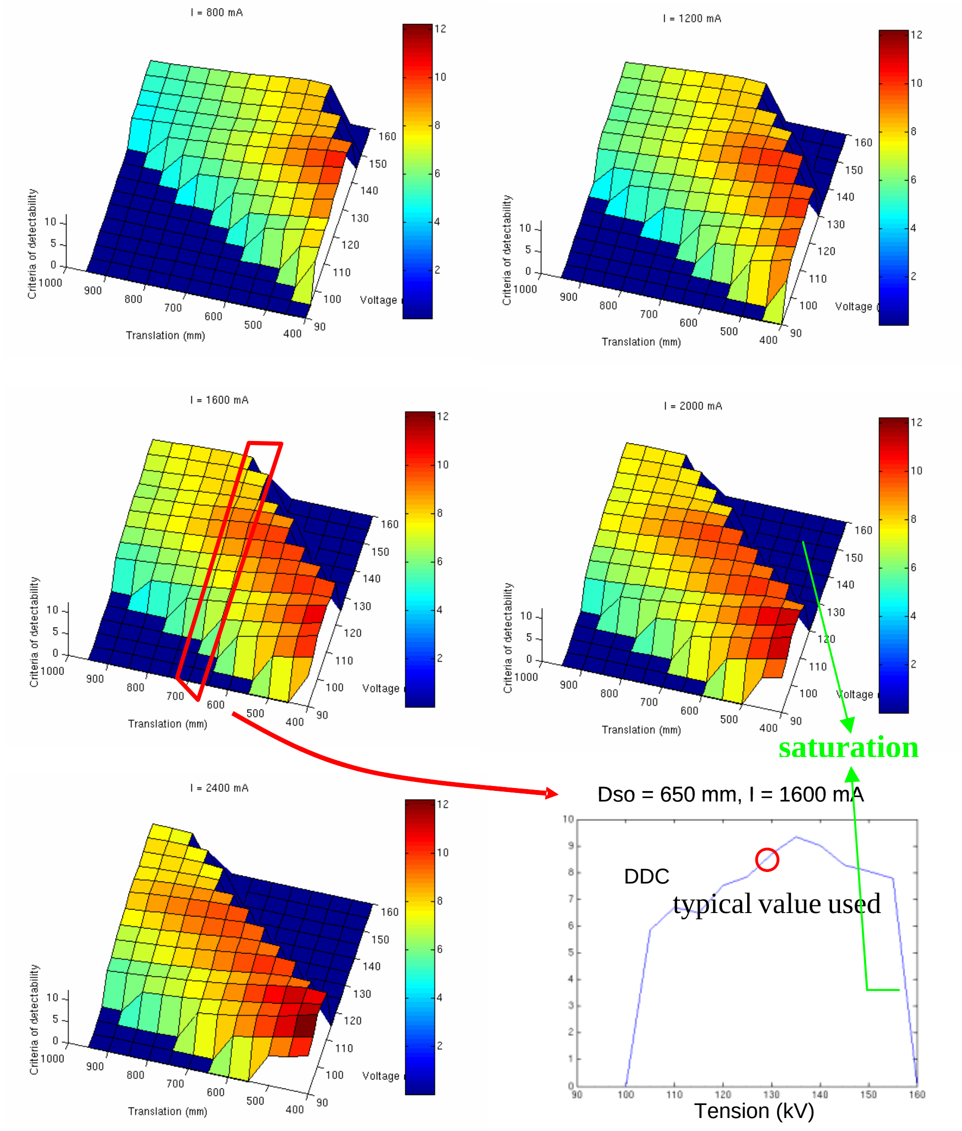

Figure 6: optimization surfaces get for the stiffener part inspected with the film M100 (no scatter simulation).

The saturation phenomenon is clearly seen on both sides of the surface, it fall to 0 due to minimum and maximum values of optical density (1 and 4). The *DDC* increases with the emitted dose, that is to say when the voltage increases, or the intensity increases, or the distance source-object decreases. This can be explained by photonic noise. The optimization surfaces arise diagonally because both distance source-film and voltage play on the emitted dose. When looking together all parameters, the highest CCD is found for lowest voltages (100 kV) – actually, low energies make the contrast increase.

Figure 7 presents the simulated images for the optimal configuration according to OPTIM3D and the one used by SNECMA. For both, the optical density is similar and correct (around 2.9) and the *DDC* criteria is quite good (respectively 11.1 and 7.8).

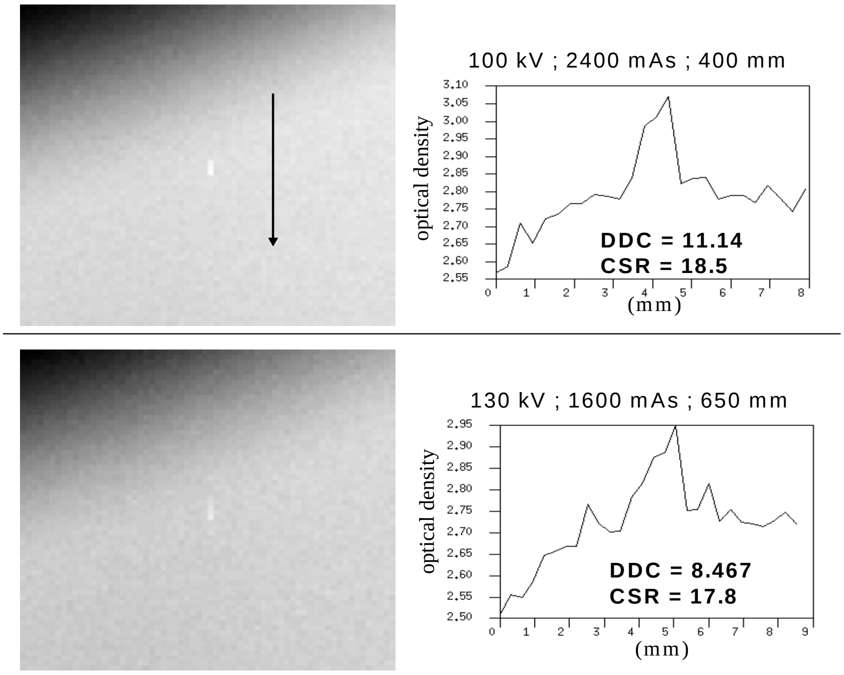

Figure 7: Simulated images for the optimal configuration (no scatter) and the usual configuration.

Others experiments have been carried out for a fan blade (SNECMA), a turbine blade (ROLLS ROYCE) and a pinion (TURBOMECA). Simulations have been performed in analytical mode and with Monte Carlo simulation of scattering radiation. The configurations regularly used by the industrials have shown to be close to the optimal configurations determined by OPTIM3D [5].

5. Conclusion

We have developed an automatic tool to find the optimal acquisition parameters set of a radiographic inspection. This tool has been implemented within Sindbad framework, leading to the OPTIM3D module. Thanks to Sindbad, simulations are considering various disturbing phenomena, focal source blurring, non perfect detector response, scattering radiation. Given an industrial part with a specific defect, the set of possible parameters is scanned exhaustively, but in a multi-resolution scheme to save time. The cost function used in the optimization scheme is based on a defect detection criteria, computed by image processing algorithms. It has been completed by a visual criteria, to take into account the human vision detectability.
OPTIM3D implementation has been optimized, by taking benefit of all the reusable intermediate computations. Nevertheless the computation is still time consuming, especially when simulating scattering radiation. The proposed optimization procedure could be improved to save time, especially if the number of parameters is greater than 3.
The program is available and has been validated on several configurations listed by industrial end-users. Comparison with experiments has been carried out with components from aeronautics where defects such as voids, inclusions and cracks have been added. The OPTIM3D tool is efficient to clearly identify the optimal acquisition configuration for a given object and a given type of defect.

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