Defect Detection Method in Digital Radiography for Porosity in Magnesium Castings

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Abstract. European project MAGCAST has been devoted to X-rays inspection of magnesium components of complex shapes, as used in spatial, aeronautics, or automotive industries. Porosity affects seriously casting quality, and is critical for safety parts. A radiographic system has been designed, and optimised considering the specific requirements, defect size, and component characteristics. It is composed of a stable mini-focus generator, a direct-conversion detector, and software.

In this paper we focus on the numerical method ensuring the automatic detection from the obtained radiographs. The principle consists in a subtraction of a reference image, then a defect extraction on the resulting flattened image. We propose an original algorithm to built off-line a reference image from a set of radiographs acquired using different components. The purpose is to get a completely defect-free reference image, associated to a confidence map. After subtraction of this reference image to the on-line acquired radiograph, an extraction step is performed, taken into account the residual errors due to non-perfect previous steps within the framework of a bayesian segmentation method. Characteristics on defect are also computed, to allow a later classification. Experimental validation of the method on industrial castings is discussed.

1. Introduction

Magnesium alloys are approximately 60% lighter than aluminium casting alloys and 80% lighter than steel. However, despite the tremendous advantages offered by Magnesium castings, especially in the automotive and aerospace industries, their use is being hindered by the difficulty of casting Magnesium components of consistently acceptable quality due to internal porosity - particularly in thin walled, and complex shaped castings. Internal porosity is due to small gas bubbles that form as the component cools within its die. If these pores occur in sufficient quantity or size, within critical areas of the casting, the overall structural integrity of these casts can be severely compromised. Corrosion resistance may also be altered. As these castings are typically used in high added-value and safety critical areas, it is imperative to inspect each casting individually. In continuous production, the problem is in controlling the casting process to consistently keep porosity to an acceptably low level – if not, the manufacturing plant will incur high scrap and operating costs. This requires a system capable of rapidly detecting and quantifying internal porosity in cast parts.
Obviously end-users require reliable automatic inspection of Magnesium castings. Magcast[1] project, that ended in 2004, addressed these issues. The work was conducted by a consortium of European businesses representing every stage of the supply chain, from end-users, inspection companies, supply companies, universities and research organisations.

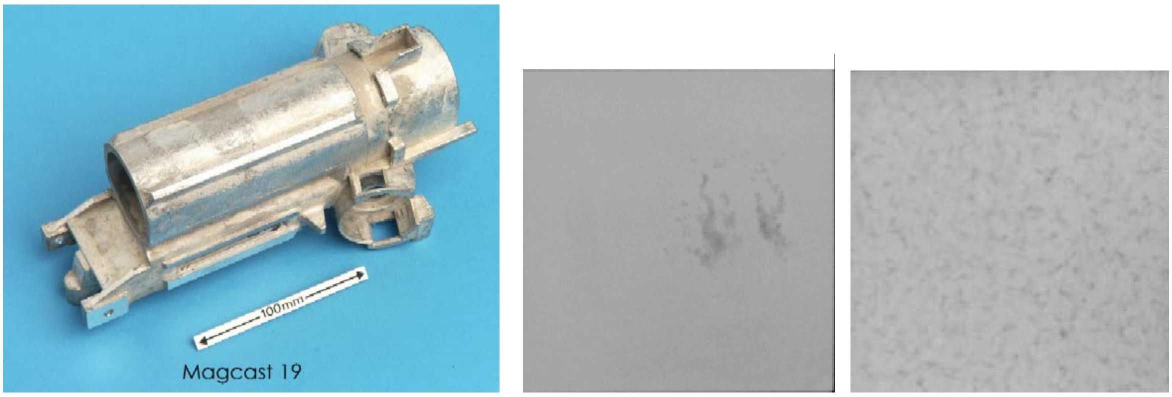

Figure 1. Typical magnesium casting, and example of porosity radiograph.

The objective of Magcast project was to create a radiographic inspection system, capable of automatically inspecting die-cast Magnesium components (Figure 1). The final result is an X-ray inspection system optimized for the application, associated to an automated defect detection software able to detect, locate and size porosity faults. The system is composed of a stabilised min-focus X-ray generator (Balteau), a direct conversion digital detector with pixel pitch 100µm (Innospexion), and an accurate manipulator (Figure 2). The defect recognition software is based on a method which description is addressed by this paper.

The Magcast system consists of:

- Stabilised min-focus radiographic X-ray generator
- Real time direct digital detector
- 8 degrees of freedom manipulator
- Automated defect recognition software

Figure 2. The rig developed within Magcast Project.

2. Defect Detection Methods in Radiography imaging

In this section we briefly review the main classes of methods for detecting flaws in components, based on digital radiographic imaging. First, notice that several modalities may be envisaged: radiography, multi-radiography, tomography [1]. Unlike usual radiography, methods based on more than one view can provide the 3D location of the defect. Furthermore, 3D combination can increase robustness in the detection itself. Generally detection is performed on each view and followed by geometrical combination of defect projections. Tomographic reconstruction requires a lot of views, but provides a volumetric description on which a 3D detection algorithm can be applied. All these methods require geometrical calibration of the system. Accuracy of result depends on mechanics accuracy. The choice of the modality depends on industrial constraints, especially examination time. In the follow up of this article we will consider the defect

detection methods for radiography, i.e. appliable on one radiograph, but the result in terms of defect mask and characteristics can be later combined using several point of views.
A lot of methods for defect detection can be found in literature, but a few of them have been successfully implemented, validated within industrial context, and proved sufficient robustness. Our purpose is not to carry out an exhaustive analysis of all the methods (see for instance [2]) but to focus on their specificities. Algorithms design for defect detection depends on casting characteristics (presence of structures, manufacturing tolerances), defects characteristics, acquisition parameters (source, detector, system stability and reproducibility), accuracy of mechanical positioning, examination constraints (maximum number of views, duration of inspection).
A first approach consists in the application of specific process to extract directly the defects from the image, for instance a DOG filter or the morphological top-hat transform, detecting small blobs of minimum level from the background. The applied filter should not extract features that are not defect, mainly pieces of the component structure. Generally a sorting step allows the elimination of these false alarms. It can be done at image level, or at characteristics level, using more or less complex decision process (from a simple test to elaborate neural network algorithm). This approach is only convenient for simple cases - constant thickness component without structures, and for small size defects.
The other methods generally proceed by flattening the image using background subtraction, and then extracting disparities. Let us call "reference image" this subtracted background. We can organize the methods depending on the nature of this reference:

- Reference image built using parametric model *(without off-line acquisition)*

A parametric model is used to simulate background, and its parameters are initialised from current image to be analysed. Only convenient for particular cases, as welding [3].

- Reference image based on simulation *(without off-line acquisition)*

A reference image is simulated from CAD model, if available [4]. This technique is time-consuming, and difficult to tune when integrating all the disturbing phenomena.

- Reference image get by filtering the current one *(without off-line acquisition)*

The most commonly applied filter is a spatial median one, with a mask size larger than the defect size. But the median filter also detects features as corners. Thus improvements have been proposed [5] [6], leading to the ISAR system certified in several industrial contexts (BMW and AUDI, 1999). This approach is very efficient for small defects. No prior information is required except defect size.

- Reference image from the current one with learning process *(with off-line acquisition)*

A filter as the median one is applied on the image, but with a mask that is adjusted to local content (structures). Other filters can be preferred. The masks design is performed using radiographs previously acquired. The off-line learning phase is then a crucial point. The system PXV5000 is based on this principle. Initially developed by Philips Industrial Xray GmbH [7], it is used for YXLON systems. The learning phase is time-consuming, and the method sensitive to non perfect geometric positioning. A more recent "non local" filter, but with such a learning phase, has been presented [8].

- Reference image from previously acquired ones *(with off-line acquisition)*

A radiograph previously acquired of a defect-free component is used directly as reference image (said golden image). If no process is applied previously to subtraction, it is obvious that a lot of constraints exists: reproducibility of the acquisition conditions, of the shape of the component (manufacture tolerance), and accuracy of both manipulator and object holder. Furthermore, this approach assumes that defect-free components are available.

3. The proposed approach

The geometry of magnesium casts may be complex. Defects are of any size and shape, typically composed of gas bubbles, or shrinkage porosity of labyrinth channels shape. The image background can not be modeled by a parametric shape Thus a simple process or specific filtering for defect extraction can not be applied in our context. Magcast rig has been designed to assume a good repeatability, in terms of mechanics but also acquisition (stability of the generator, linearity of the detector). For these reasons, we propose to use a reference image, or *golden* image, and to compare it with the current radiograph to be analyzed. To avoid a tedious learning step, we propose to use this reference image numerically for background subtraction. In this case, we have to perform a matching in terms of attenuation levels and geometry between current image and reference one, previously to their comparison, and to design an extraction algorithm, taking into account residual errors due to non perfect matching. Furthermore we have to be provided with defect-free reference image. The different phases of the method are detailed hereafter.

3.1 Building an artificial reference image

One key point is to obtain a porosities-free reference image, which has been shown experimentally to be rarely true. Another goal is to get information about the variability of the acquired images. We propose to acquire reference images from a set of components. Once a geometrical configuration is given, the castings are successively put on the platform and the radiographs are acquired, without any mechanical motion. Acquisition conditions are stable during the experiment. The variability between radiographs mainly results from uncertainty of positioning, and difference between the parts due to manufacturing tolerances. The simplest way to use such a set of reference images is to store them, and to compare on-line the current image with this set, choosing the closest according to one criteria. We propose another approach, aiming at building a defect-free artificial reference image, from the set of acquired ones. Acquired radiographs are combined by a numerical process based on the set of values of a given pixel through the different acquired reference images. Let us consider the 1D vector constituted by the list of values of a given pixel. If it is located inside a defect on one radiograph, the corresponding value will be an outlier. If the pixel is located near an edge, the values of the vector fluctuate a lot. If it belongs to a locally homogeneous area, the values are slightly varying due to noise.

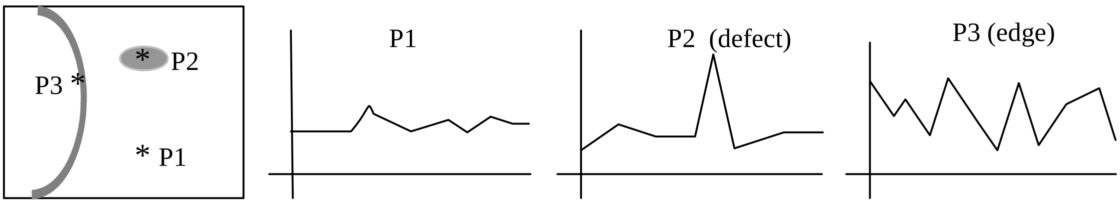

Figure 3. Behavior of a pixel in background (P1), in a defect (P2) and at an edge (P3).

On this list of values we apply a median filter, to obtain an “artificial” reference image. From the 1D vector composed of the pixel values through the reference images, we also compute the standard deviation, to reflect the variability of these values, so mainly the presence of edges. In case of a high variability, the defect detection will be less confident. After spatial smoothing and normalization, we get a confidence map. Finally we get a reference image, where structures are slightly blurred, without any defect or small imperfection, representing the common information of the acquired radiographs from several components, associated to a confidence map. Example is given in Figure 4.

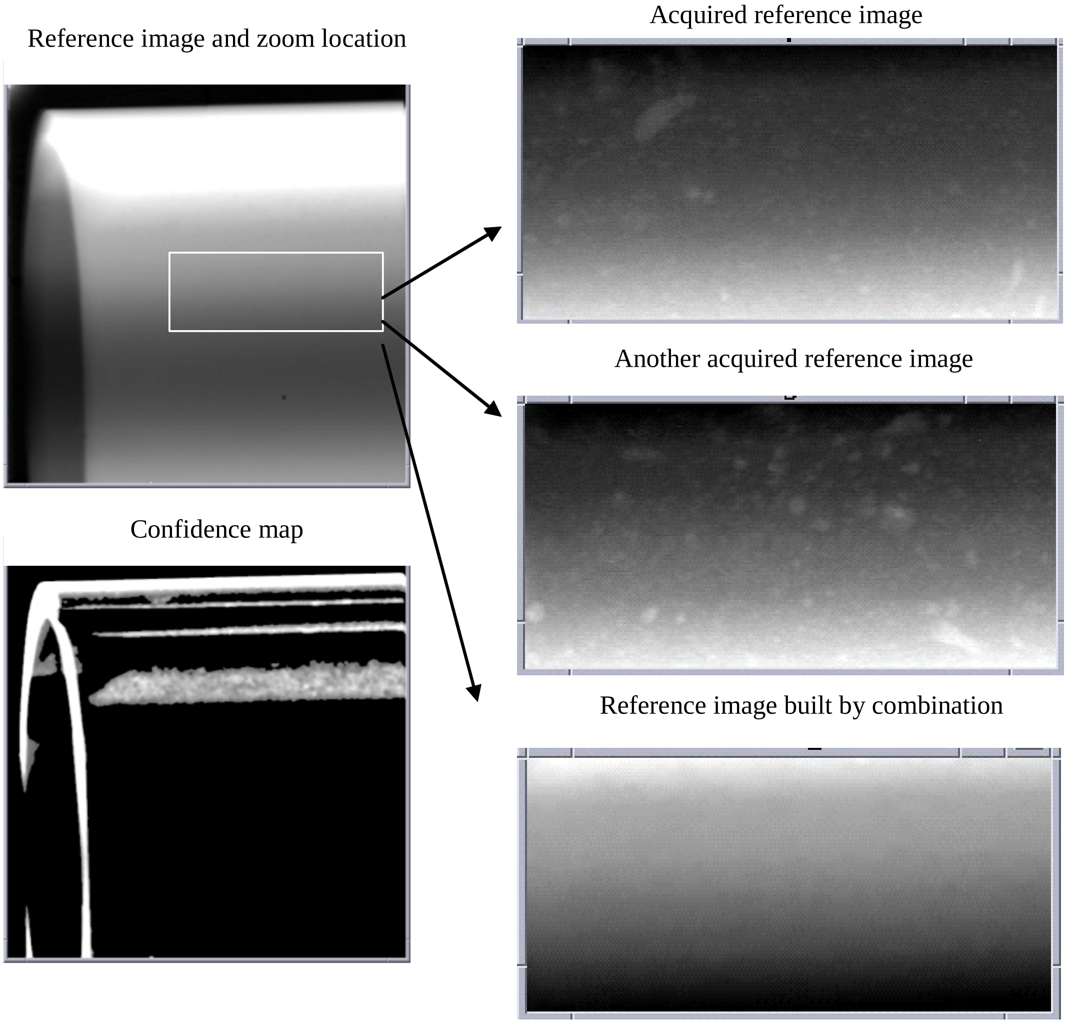

Figure 4: Reference image built from different acquired reference images.

3.2 Defect extraction

When analyzing a radiograph on-line, we are provided with the current image *I*, the reference image $I_{reference}$, and associated confidence map $I_{confidence}$. First, an adaptation between the attenuation levels of *I* and $I_{reference}$ is performed, using histogram comparison. Geometrical misalignment could come from uncertainty in component handling, in system mechanics, and geometrical tolerance in component manufacturing. Mechanics is usually composed of translation, rotation and tilt. Notice that these motions, especially rotation, may induce non-linearities in the apparent displacement in the projected image. Consequently, the registration methods based on translation models are not convenient. A specific one devoted to structured castings [9] have been tested and provides non convincing results on Magcast components, especially if a Region of Interest has been specified in a small area outside the structures. Finally we do not perform any registration. The unavoidable misalignment will be taken account by the use of the confidence map presented above, and if required (depending on the system) the use of an optional 3D distance. A 3D distance between two images generalizes the usual 1D distance equivalent to a difference (distance in grey level for each pixel). It does not consider only the difference of the two image values for the considered pixel, but also the difference with the values of neighboring pixels. It is implemented by a local operator defined from a 3*3*3

cubic mask M giving the distance from a pixel to its adjacent neighbors in 3 directions (26 neighbors). This 3D distance is optional, and is used depending on geometrical accuracy, especially of object handling. Finally we get $I_{difference}$ image.
This difference image contains the defects, but also noise, and false alarms mainly due to the fact that images are not perfectly comparable, especially close to the edges. Let us try to characterize a defect: a pixel belonging to a lack-of-material defect corresponds to a high value in $I_{difference}$ (brighter than the local mean value), a high contrast in $I_{difference}$, and a low confidence value. To get the contrast information, we first apply a contrast enhancement process. A lot of methods exist for computing contrast filtering. We have chosen one that is fast, takes into account multi-directionality, and considers an adjustable spatial size.
Then we model the detection problem by a labeling process, where the possible labels are 1 for defect / lack of material, -1 for defect / excess of material, and 0 for background. The previous property can be expressed by the combination rule (with opposite signs in case of excess of material): $label(P) = 1 \Leftrightarrow \begin{cases} I_{difference}(P) >= Thresh1 \\ I_{contrast}(P) >= Thresh2 \\ I_{cconfidence}(P) <= 0.5 \end{cases}$

where the two thresholds can be related to the minimum contrast of the searched defects, which depends directly on the energy of the X-rays and the minimum thickness of defect by: $Contrast_{\min} = \mu_{magnesium}(E) \cdot thickness(defect)$.
Figure 5 shows examples of I, $I_{difference}$, and $I_{contrast}$ (final image will be commented later).

The final image contains the masks of defects (white) and alarms (black) superimposed on the initial image

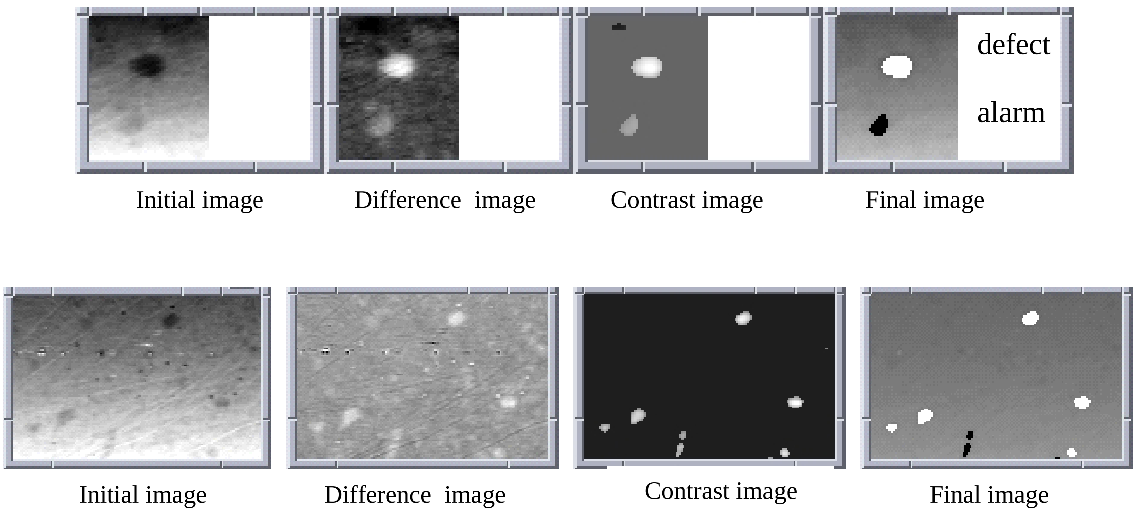

Figure 5: Two examples of combination of information for the detection process.

By applying this decision rule, we get noisy resulting image, especially because neighboring effect has not been taken into account. Obviously, defects are composed to several connected pixels. We propose to apply a regularization framework, where the solution is obtained as the result of an "energy" minimization [10, 11]. The *observations* are composed of the difference image, the contrast image and the confidence map. A Bayesian formulation allows to formalize the problem by:

$$\text{minimize}\left(\lambda_s \cdot E_{spatial}(I_{label}) + \lambda_d \cdot E_{difference}(I_{difference}, I_{cfd}) + \lambda_c \cdot E_{contrast}(I_{contrast}, I_{cfd})\right)$$

A Markovian model is used to represent local spatial context, so to express $E_{spatial}$. The other terms $E_{differncee}$ and $E_{contrast}$ measure the cost of difference and contrast observation knowing one label configuration. $\lambda_s, \lambda_d, \lambda_c$ are weighting coefficients. The minimisation is performed using a deterministic algorithm with a fixed number of iterations. Finally, on the image of labels, a standard connectivity analysis is performed to extract defects masks.

3.3 Defect Characterization and localization

The result of the previous step consists in a list of *alarms* rather than defects. Two sets of characteristics are then computed: a first set, mainly contrast characteristics, allows to sort the alarms. A second set, essentially shape and attenuation parameters, are computed only for defects that have been distinguished from false alarms. The purpose of this second set is to provide information required for further characterization and classification step. This parameters computation uses the image of labels, the initial image, and the difference one.

<u>Contrast parameters (for alarm sorting)</u>

A first group of parameters is computed using a "binary ring" get by morphological dilatation of the mask of the defect, and comparing the mean value in this ring and the one inside the defect, on the different images. This is no more a *pixel* contrast but a *region* contrast. We also compute contrast parameters inspired by D.Mery, and his parameter "Crossing line Profile" [12]. The purpose is to measure the variability of the different directional contrasts. We consider the 4 main directions, and for each one, the image profile which is flattened by subtracting the line relying the profile limits. Then we choose the contrast of the most homogeneous profile. We have slightly change this parameter to be more adapted to the shape of the alarm mask, taking this shape into account when computing the border of the analyzed profile, when Mery considers a fixed size window. This contrast parameter has shown to be very useful for false alarms that are due to non-perfect alignment of edges. A decision rule is applied to sort the alarms. For a lack-of-material defect, the ring contrast should be highly negative on initial image, highly positive on $I_{difference}$, small on $I_{reference}$, and Mery-like contrast highly negative on initial image.

<u>Parameters for defect characterization</u>

We propose a list of the most standard characteristics. We compute the usual geometric parameters: surface, center of gravity, minimum and maximum bounds. To describe the shape more precisely, we add the following parameters based on second order moments: inertia, elongation and orientation, plus the axis of the equivalent ellipse, and an occupation ratio. All these parameters can be computed on the binary defect mask, or being weighted by the image grey levels. Notice that some of these shape parameters are of non interest for small defects of a few pixels size. We compute grey levels characteristics: mean value and standard deviation. Mean value on the difference image corresponds to the mean thickness of the defect. We have also added a measure of the local 3D curvature of the grey levels surface, which is significant for large defects only.
To that list, we add the contrast parameters previously discussed.

<u>Defect localization</u>

Defect localization is based on classical stereoscopic method. At least two radiographs are acquired with different points of view, without moving the component out of the platform The accuracy involved in the computation concerns only the motion axes of the system. When a defect is detected on at least two views, the 2D locations of its projected masks allow to determine a 3D location, thanks to the acquisition parameters of each view, and to the calibrated geometric parameters of the system.

4. Experiments and results

The developed rig has been used for experimental validation. Radiographs are provided after elimination of bad pixels. Typical component can be seen in Figure 1.
A Region-of-interest can designed by the user, as part of the inspection plan. Defect detection in then applied only in the specified area. If the ROI is carefully chosen without any edge inside it, the method that we propose can be simplified, in particular the 3D-distance and the confidence map are no longer useful. The parameters of the method can be easily tuned. In fact they are automatically computed from a few physical characteristics, the minimal size of searched defects, and their minimal contrast (related to their thickness).
We present now (Figure 6) two examples of detection process. The final image contains the masks of defects (in *white*) and alarms (in *black*) superimposed on the initial image. Difference and contrast images are shown. It is clear when considering the difference image than a simple thresholding would not provide correct results.

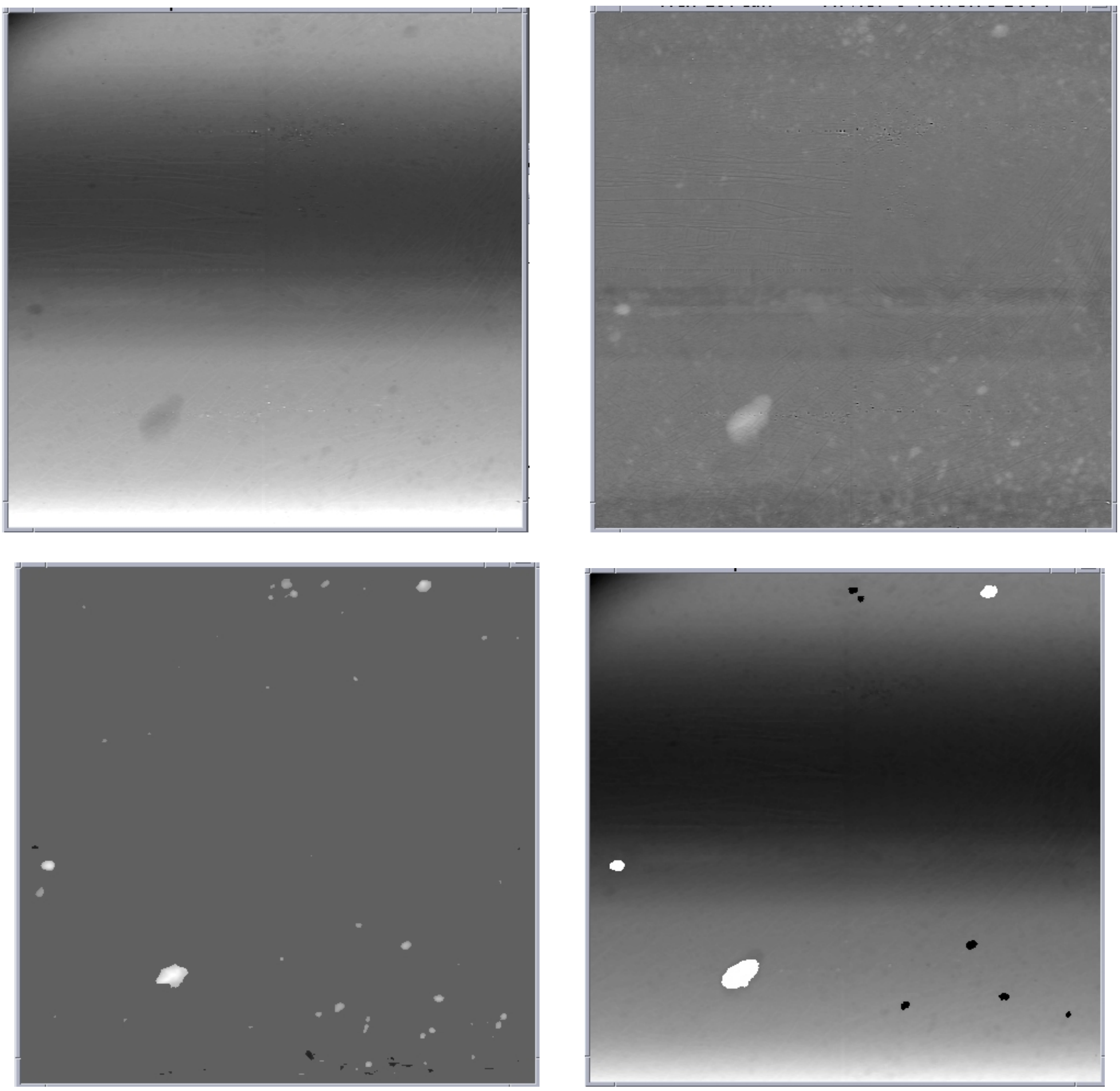

Figure 6: Example of defect detection process (Initial, difference, contrast, and final image).

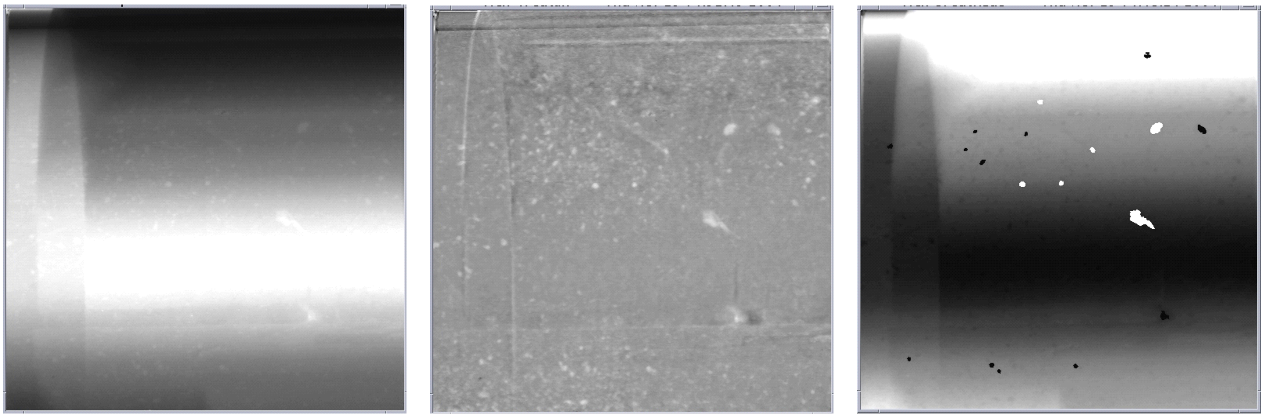

Figure 7: Example of defect detection process (Initial, difference, and final image).

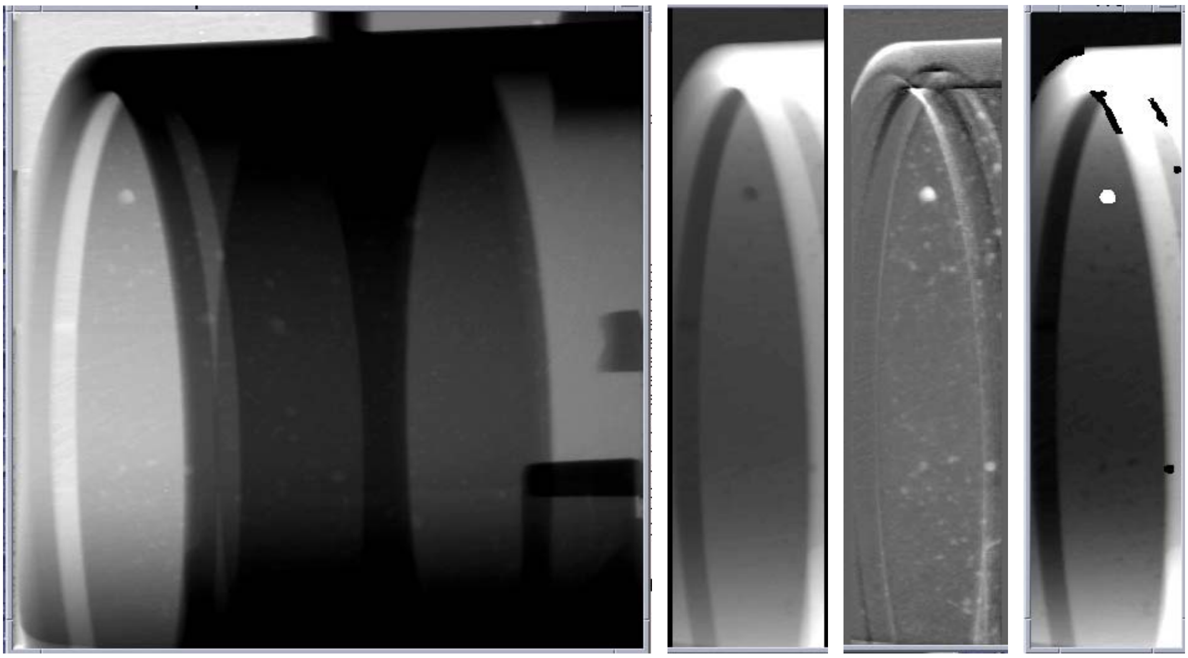

Figure 8: Example of defect detection (Full flux image, ROI on initial, difference, and final image).

When considering the final images presented in Figure 6, 7, and 8, we observe that the method has correctly detected the set composed of defects plus false alarms. The distinction between both is less obvious. Artefacts due to cast structures have been correctly classified in alarms (figure 8), but some false alarms in figures 6 and 7 are perhaps true defects. Parameters used for alarm sorting should be tune more precisely. It has to be done in collaboration with industrial end-users, because this tuning in fact integrates prior information. Experiments and comparison with expert decision are obviously required.

5. Conclusion

We have presented the X-ray system that has been developed within European project MAGCAST, devoted to the inspection of magnesium components of complex shape. We have focused on the numerical method ensuring the automatic detection from the obtained radiographs. We propose an original algorithm to built off-line a reference image from a set

of radiographs acquired using different components, and a specific defect extraction method. Both have been proved to be very sensitive to small defects.
A list of defect characteristics is provided. To allow a classification, additional information has to be provided by the end-user, depending on each context. If required, the method should be completed to deal with cluster defects (group of several individual detected defects). Another extension would concern the localization aspect, needed when a lot of masks are detected on each view, by developing a complex matching process of the masks.
The current state of the software is a useful tool, to be adapted to each industrial context.

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