Automated Multiple View Inspection of Metal Castings

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ABSTRACT

Automated visual inspection of metal castings is defined as a quality control task that determines automatically if a casting deviates from a given set of specifications using visual data. Many research directions in this field have been exploited, some very different principles have been adopted and a wide variety of algorithms have been appeared in the literature. However, the developed approaches are tailored to the inspection task, *i.e.*, there is no common approach applicable to all cases because the development is an *ad hoc* process. Additionally, detection accuracy should be improved, because there is a fundamental trade off between false alarms and miss detections. For these reasons, we proposed a novel methodology, called *Automated Multiple View Inspection*, that uses redundant views of the test object to perform the inspection task. The method is opening up new possibilities in inspection field by taking into account the useful information about the correspondence between the different views. It is very robust because in first step it identifies potential defects in each view and in second step it finds correspondences between potential defects, and only those that are matched in different views are detected as real defects. In this paper, we review the advances done in this field giving an overview of the multiple view inspection and showing experimental results obtained on metal castings.

Keywords: Non-destructive testing, automated visual inspection, X-ray testing.

1. INTRODUCTION

Metal castings produced for the automotive industry, such as wheel rims, steering knuckles and steering gear boxes, are considered important components for overall roadworthiness. Shrinkage as molten metal cools during the manufacture of die-castings, can cause non-homogeneous regions within the work piece. These are manifested, for example, by bubble-shaped voids or fractures (see some examples in Fig. 1). Voids occur when the liquid metal fails to flow into the die or flows in too slowly, whereas fractures are caused by mechanical stresses when neighboring regions develop different temperature gradients on cooling. Other possible casting discontinuities include inclusions or slag formation. To ensure the safety of construction, it is necessary to check every part

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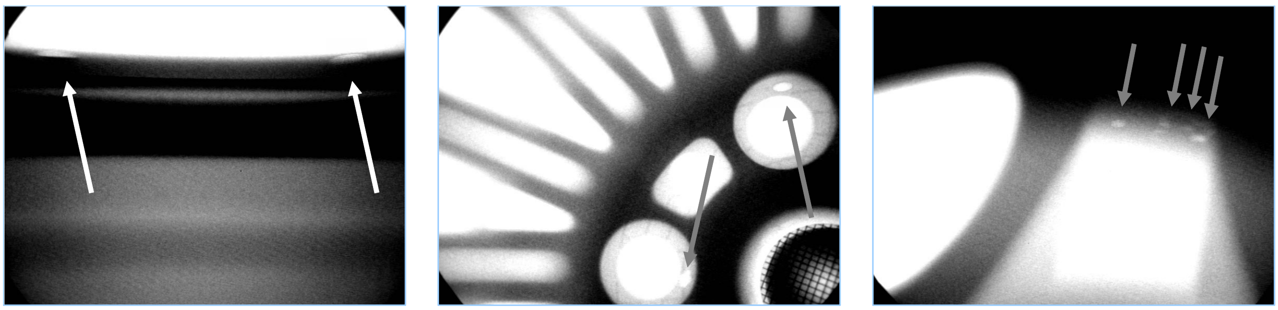

Figure 1. Radioscopic images with defects (see arrows).

thoroughly using non-destructive testing like radioscopy, which rapidly became the accepted way for controlling the quality of die cast pieces.

Metal castings inspection is defined as a quality control task that determines if a casting deviates from a given set of specifications using visual data. Inspection usually involves measurement of specific part features such as assembly integrity, surface finish and geometric dimensions. If the measurement lies within a determined tolerance, the inspection process considers the product as accepted for use. Usually, metal castings inspection was performed by human inspectors, nowadays, however, inspection based on computer vision has been gradually replacing more and more human inspection. Although humans can do the job better than machines in many cases, they are slower than the machines and get tired quickly. Additionally, human inspectors are not always consistent and effective evaluators of products because inspection tasks are monotonous and exhausting, even for the best-trained experts. Typically, there is one rejected in hundreds of accepted products. Moreover, human experts are difficult to find or maintain in an industry, require training and their skills may take time to develop. Compared to a manual evaluation of X-ray images, automated detection of casting defects offers the advantages of objectivity and reproducibility for every test. In recent years, automated radioscopic systems have not only raised quality, through repeated objective inspections and improved processes, but have also increased productivity and profitability by reducing labor costs.[1]

According to comprehensive reviews on general automated visual inspection[2–5] the developed approaches are tailored to the inspection task, *i.e.*, there is no common approach applicable to all cases because the development is an *ad hoc* process. Additionally, detection accuracy should be improved, because there is a fundamental trade off between false alarms and miss detections.

A comprehensive review on automated inspection of castings[6] shows a similar situation. In order to inspect the whole object, radioscopic images at different positions of the casting are taken and processed. The classic image processing methods for flaw detection[7–9] consist of a bank of filters which generate an error-free reference image from the radioscopic image taken. Flaws are detected at pixels where the difference between them is considerable. Using a priori knowledge of the regular structures of the castings, each programmed view is subdivided into several segments to enable the use of the best type of filter for each part of the image. Varying the matrix size and the directions of the mask filters, they can be adapted to the regular structures of the specimen. This procedure is repeated at each programmed position of the casting. The disadvantages of these methods are as follows: a) The filters must be configured and tuned manually for each casting and position. If the casting is not exactly placed at the required position, the filter might not work correctly and the detection may fail. b) The filter parameters, like size and direction of the filter mask, depend strongly on the size and shape of the structure of the casting. c) Useful information about the correspondence between the different views of the casting is not taken into account.

Other methods, such as the combined median filter,[10] the intelligent knowledge based technique,[11] the feature based approach,[12] and the neural networks procedure,[13] attempt to detect flaws without a priori information about the location of regular structures. The prerequisite for the use of a method from this group is the existence of common properties which define all casting defects well and also differentiate them from design features of the test pieces. These prerequisites are often fulfilled only in special testing situations. For this reason, the true positive and false positive rates of these methods seem to be unsatisfactory in order to gain acceptance in industry.

Our research and development on metal castings inspection is, however, on going into automated adaptive processes to accommodate design modifications, and into redundancy in visual information to improve the performance. We develop a novel methodology called Automated Multiple View Inspection (AMVI). The method uses redundant views to perform the inspection task of metal castings. This methodology is opening up new possibilities in inspection field by taking into account the useful information about the correspondence between the different views of the test object. A first version of AMVI[14] with the aid of monocular image sequences was presented for the quality control of aluminum castings of the automotive industry using X-ray images. In contrast to the classic inspection methods that analyze individual images, AMVI detects defects by analyzing multiple views of the same part taken from different viewpoints. Thus, AMVI is similar to the way a (human) inspector examines a test object: first, the inspector detects anomalous details in an image sequence obtained from the test object in motion; and second, the inspector tracks in the image sequence the irregularities detected

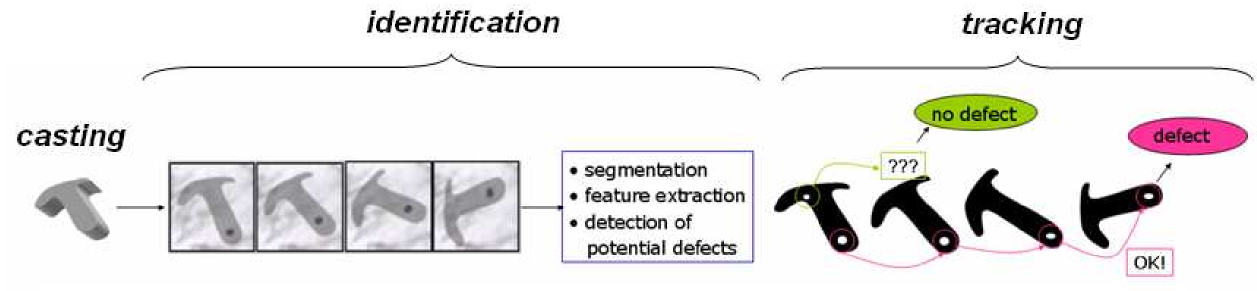

Figure 2. AMVI Strategy: The tracked potential defects are considered defects, the non tracked potential defects are considered noise.

in the first step. If the inspector can track them, *i.e.*, if the irregularities are visible among the image sequence, he or she classifies the test object as defectively. Similarly, the suggested computer-aided method AMVI is able to detect defects in two steps (see Fig. 2). In the first step, called *identification*, potential defects are automatically identified in each image of the sequence using a single filter and no a priori knowledge of the structure of the test object. In the second step, called *tracking*, an attempt is made to track the identified potential defects in the image sequence. Therefore, only the existing defects (and not the false detections) can be successfully tracked in the image sequence because they are located in positions dictated by the motion of the test object. Thus, two or more views of the same object taken from different viewpoints can be used to confirm and improve the diagnostic done by analyzing only one image. A similar idea is also used by radiologists that analyze two different view X-rays of the same breast to detect cancer in its early stages. Hence, the number of cancers flagged erroneously and missed cancers may be greatly reduced, see for example a novel method[15] that finds automatically correspondences in two different views of the breast is presented.

The key idea of this multiple view analysis is to gain more information about a test object by processing images taken at different viewpoints. It is a useful and powerful alternative for examining complex objects were uncertainty can lead to misinterpretation, because two or more views of the same object taken from different viewpoints can be used to confirm and improve the diagnostic done by analyzing only one image.

The first AMVI strategy was successfully implemented for calibrated image sequences.[14] However, it is not simple to implement it in industrial environments because the calibration process[16] is a difficult task and unstable. In order to avoid the mentioned disadvantages, we developed new AMVI strategies[17,18] based on the tracking of potential detects in uncalibrated image sequences. The new approaches tracks the potential defects based on a motion model estimated from the image sequence self.

In this paper, we review the advances done in this field giving an overview of the multiple view inspection and showing experimental results obtained on metal castings. The rest of the paper is organized as follows: Section 2 summarizes the inspection of metal casting in terms of hardware and software. Section 3 presents the AMVI methodology showing the calibrated and uncalibrated approaches. Section 4 shows preliminary results obtained with the proposed methodology. Finally, Section 5 gives concluding remarks and perspectives for future works.

2. INSPECTION OF METAL CASTINGS

The principle aspects of an automated X-ray inspection unit[6] are shown in Fig. 3. Typically, it comprises the following five steps: i) a *manipulator* for handling the test piece; ii) an *X-ray source*, which irradiates the test piece with a conical beam to generate an X-ray image of the test piece; iii) an *image intensifier* which transforms the invisible X-ray image into a visible one, iv) a *CCD camera* which records the visible X-ray image; and v) a *computer* to perform the digital image processing of the X-ray image and to classify the test piece accepting or rejecting it. The computer may also control the manipulator for positioning the test piece in the desired inspection position, although this task is normally performed by a programmable logic controller (PLC). Nowadays, flat amorphous silicon detectors[19] are used as image sensors in some industrial inspection systems.

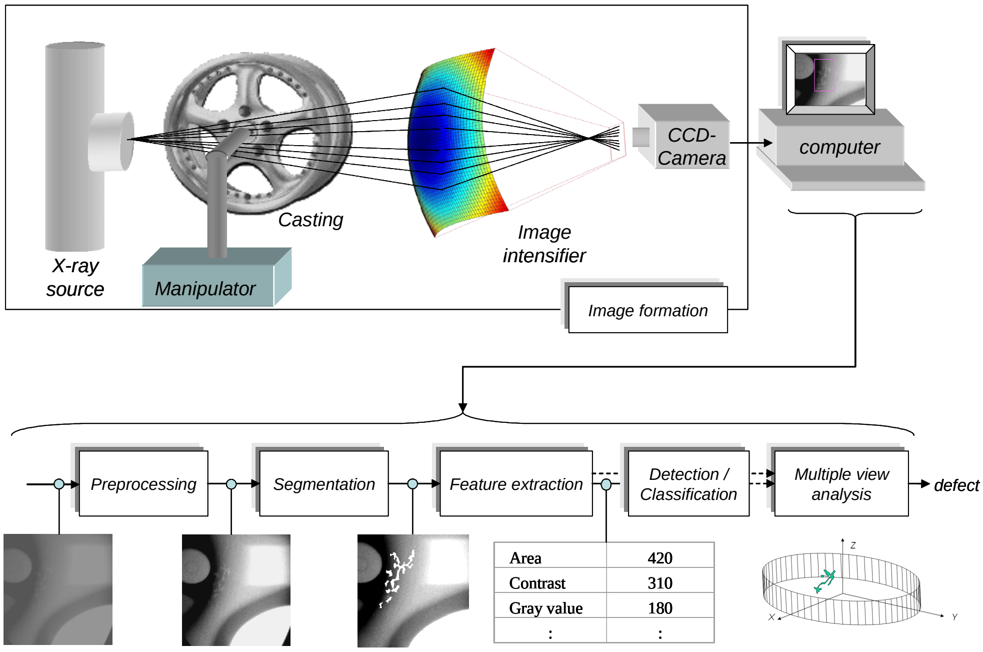

Figure 3. Schematic diagram of an automated X-ray testing stand.

In such detectors, using a semi-conductor, energy from the X-ray is converted directly into an electrical signal (without image intensifier). In X-ray examination, X-ray radiation is passed through the material under test, and a detector senses the radiation intensity attenuated by the material. A discontinuity in the material modifies the expected radiation received by the sensor.[20]

In an X-ray image we can see that the discontinuities, such as voids, cracks and bubbles (or inclusions and slags), show up as bright (or dark) features. The reason is that the X-ray attenuation in these areas is shorter (or higher). The contrast in the X-ray image between a defect and a defect-free neighborhood of the specimen is distinctive. Hence, according to the principle of differential absorption[20] the detection of discontinuities can be achieved automatically using computer vision techniques that are able to identify unexpected regions in a digital X-ray image.

In the computer-aided inspection of castings, our aim is to identify discontinuities automatically using computer vision techniques. The general automated inspection process, presented in Fig. 3, consists of image formation, preprocessing, segmentation, feature extraction, detection/classification and multiple view analysis. The existing inspection methods[6] follows at least two steps of the general schema presented in Fig. 3 (*image formation* and *segmentation*). However, since our approach uses pattern recognition and multiple view techniques, we show the general schema with the mentioned six steps:

• *Image formation*: An X-ray image of the casting under test is taken and stored in the computer. The X-ray image is usually captured with a frame-grabber and stored in a matrix. The eye is only capable of resolving around 40 grey levels,[21] however for the detection of discontinuities in aluminum castings, grey level resolution must be a minimum of 2^8 levels. In some applications 2^{16} grey levels are used, which allows one to evaluate both very dark and very bright regions in the same image.[19]

• *Image preprocessing*: The quality of the X-ray image is improved in order to enhance the details of the X-ray image. Usually, the pre-processing techniques are used to remove noise, enhance contrast, correct the shading effect and restore blur deformation.

• *Image segmentation*: The digital images is divided into disjoint regions with the purpose of separating the parts of interest from the rest of the scene. The idea is to segment those regions that correspond to the defects of the specimen.

• *Feature extraction*: Since some structural parts of the object could be erroneously segmented as defectively regions in previous step, they are denoted as *potential* defects. Subsequently, additional steps are required to eliminate the false alarms of the potential defects. The first of these steps is feature extraction, which is centered principally around the measurement of geometric properties and on the intensity characteristics of regions. It is important to know which features provide information about discontinuities. With this end, a feature selection is carried out to find those features that best describe discontinuities, eliminating for example features that are correlated or provide no information whatsoever.

• *Detection/classification*: The extracted (and selected) features of each region are analyzed in order to detect or classify the existing defects. We will differentiate between the *detection of discontinuities* and the *classification of discontinuities*. Detection corresponds to a binary classification, because in the detection problem, the classes that exist are only two: 'discontinuities' (defects) or 'regular structures' (no defects), whereas the recognition of the type of discontinuity (e.g., voids, cracks, bubbles, inclusions and slags) is known as classification of discontinuity types.

• *Multiple view analysis*: Multiple view geometry[22] is increasingly being used in artificial vision. It describes explicit and implicit models which relates the 3D coordinates of an object to the 2D coordinates of the digital image pixel, the geometric and algebraic constraints between two, three and more images taken at different projections of the object, and the problem of 3D reconstruction from N views. Since in last step (detection/classification) certain 'no-defects' could be classified erroneously as 'defects', we use multiple view geometry as a final discrimination step. The key idea is to gain more information about the test object by analyzing multiple views taken at different viewpoints. Thus, the attempt is made to match or track the remaining potential defects along the multiple views. The existing defects can be effectively tracked in the image sequence because they are located in the positions dictated by geometric conditions. In contrast, false alarms can be successfully eliminated in this manner, since they do not appear in the predicted places on the following images and, thus, cannot be tracked. The tracking in the image sequence is performed using algebraic multi-focal constraints: bifocal (epipolar) and trifocal constraints[22–24] among others. They are used to ensure the location of corresponding points in different views. Multiple view analysis is a useful and powerful alternative for examining complex objects were uncertainty can lead to misinterpretation, because two or more views of the same object taken from different viewpoints can be used to confirm and improve the diagnostic done by analyzing only one image. The multiple view analysis will be explained in Section 3.2 in further detail.

3. AUTOMATED MUTIPLE VIEW INSPECTION

Motivated by visual inspections (that are able to differentiate between regular structures and discontinuities by looking at a moving radioscopic image), we developed a method[14] based on geometric computer vision algorithms[22] that considers X-ray images taken at different viewpoints. The procedure is able to perform casting discontinuity detection automatically in two stages, as shown in Fig. 2, with a single filter and without a priori knowledge of the test piece structure. In next sections we outline the two stages in further details.

3.1. Identification of Potential Defects

According to Fig. 3, the identification of potential defects is performed after preprocessing, segmentation, future extraction and detection/classification steps. The segmentation of potential defects identifies regions in each image of the sequence that may correspond to real defects. Two general characteristics of the defects are used to identify them: a) a defect can be considered as a connected subset of the image, and b) the grey level difference between a defect and its neighbourhood is significant. The potential defects are identified without a-priori knowledge about the structure of the casting. First, a Laplacian-of-Gaussian (LoG) kernel and a zero crossing algorithm[21] are used to detect the edges of the X-ray images. The LoG-operator involves a Gaussian lowpass filter which is a good choice for the pre-smoothing of our noisy images that are obtained without frame averaging. The resulting binary edge image should produce at real defects closed and connected contours which demarcate *regions*. However, a defect may not be perfectly enclosed if it is located at an edge of a regular structure as shown in Fig. 4c. In order to complete the remaining edges of these defects, a thickening of the edges of the regular structure is performed as follows: a) the gradient of the original image is calculated (see Fig. 4d); b) by thresholding the gradient image at a high grey level a new binary image is obtained; and c) the resulting image is

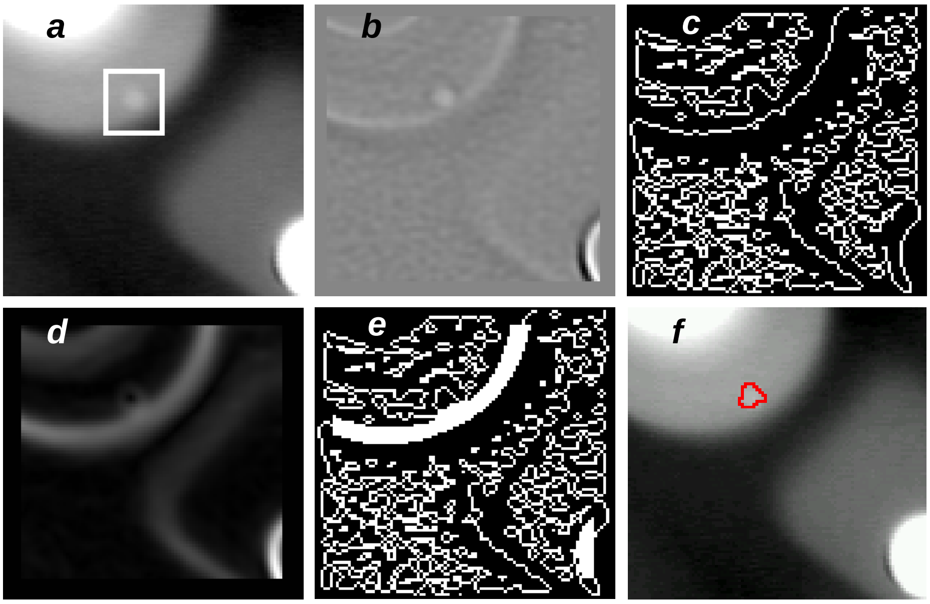

Figure 4. Detection of potential defects: a) radioscopic image with a small flaw at an edge of a regular structure, b) Laplacian-filtered image with $\sigma = 1.25$ pixels (kernel size $= 11 \times 11$), c) zero crossing image, d) gradient image, e) edge detection after adding high gradient pixels, and f) detected flaw using the variance of the crossing line profile.

added to the zero crossing image (see Fig. 4e). Afterwards, each closed region is segmented. In order to identify the potential defects, features are extracted from *crossing line profiles*[25] of each segmented region. Crossing line profiles are grey level profiles along straight lines crossing each segmented region in the middle. If the variance of the crossing line profiles is high, the segmented region is classified as potential defect. This is a very simple detector of potential defects with a large number of false alarms flagged erroneously. However, the advantages are as follows: a) it is a single detector (it is the same detector for each image), b) it is able to identify potential defects independent of the placement and the structure of the test object, *i.e.*, without a-priori information of the design structure of the test object, and c) the detection rate of real defects is very high (more than 90%).

After the segmentation, the automatic detection of discontinuities uses pattern recognition methodology with binary classification. In this problem a decision is made about whether or not an initially segmented potential discontinuity in an image is in fact a discontinuity. We outlines the binary classification problem[26] where more than 400 features are evaluated and statistical classifiers are implemented. Unfortunately, in real automatic discontinuity detection problems there are a reduced number of discontinuities in comparison with the large number of regular structures. This seriously limits the application of classification techniques such as artificial neuronal networks due to the imbalance between classes. We presented a new methodology[27] for efficient training with imbalances in classes. The premise of this approach is that if there are sufficient cases of the smaller class, then it is possible to reduce the size of the larger class by using the correlation between cases of this latter class, with a minimum information loss. It is then possible to create a training set for a neuronal model that allows good classification. Additionally, the classification problem was outlined using a neuro-fuzzy approach[28] and fusion strategies.[29] By analyzing 50 X-ray images, more than 22 000 regions were segmented, however only 60 of them were discontinuities (the rest were false alarms). Nevertheless, after the binary classification with neuronal networks, 57 of 60 discontinuities were detected, with only one ore two false alarms per image.

3.2. Tracking of Potential Defects

According to Fig. 3, the tracking of potential defects is performed using multiple view analysis.[23,24] In this second stage, an attempt is made to track the potential casting discontinuities in the sequence of images. False detections can be eliminated successfully in this manner, since they do not appear in the following images and, thus, cannot be tracked. In contrast, the true casting discontinuities in the image sequence can be tracked successfully because they are located in the position dictated by the geometric conditions. Multi-focal tensors are applied to reduce the computation time. Following a 3D reconstruction of the position of the potential casting discontinuity tracked in the image sequence, it is possible to eliminate those which do not lie within the boundaries of the test piece.

Figure 5 shows the pseudo-code of the tracking algorithm. The steps are easy to understand according to this schema:

1) In the segmentation and pattern recognition processes each identified potential defect of the image sequence is labeled with an unique number. In image p, the n_p identified potential defects are labeled as e_p, $e_p + 1$, ... $e_p + n_p - 1$ (note that $e_p + n_p = e_p + 1$). We store the coordinates of the potential defect 'a' in vector $\mathbf{x}_a$ and the features that characterize the potential defect in vector $\mathbf{x}_a$. The tracking takes place in the following three steps:

2) We look for the n_p potential defects in image p that have corresponding potential defects in the next m images (we use $m = 3$ in order to reduce the computational cost). The corresponding potential defects are those that are similar enough and are located in places that fulfill the bifocal constraints, this is evaluated in functions 'similar' and 'bifocal' respectively. If a potential defect is not matched with any other one, it will eliminated and considered as false alarm, whereas the obtained N_2 duplets are stored in matrix $\mathbf{B}$.

3) From the matched potential defects stored in matrix $\mathbf{B}$, we look for triplets that fulfill trifocal constraints. A row i in matrix $\mathbf{B}$ has two potential defects (a, b) that fulfill the criteria in two views. We look for other rows j in $\mathbf{B}$ where the first element is equal to b. Thus, we find a triplet (a, b, c). If the potential defects a, b and c fulfill the trifocal constraints ('trifocal'), we store the triplet in a new row of matrix $\mathbf{C}$. Potential defects that do not find correspondence in three views will be eliminated.

4) We repeat the last step for four views and we store the quadruplets in matrix $\mathbf{D}$. Since our detector cannot guarantee the identification of all real flaws in more than four views, a tracking in five views could lead to the elimination of those real flaws that were identified in only four views. However, if a potential flaw is identified in more than four views, more than one quadruplet can be detected. For this reason, these corresponding quadruplets are joined in a trajectory that contains more than four potential defects.[14] Further details of the tracking algorithm can be found in Ref. 30. An example is illustrated in Fig. 6.

1) Identification of Potential Defects

N_1 number of images in the sequence
e_p number of the first potential defect in image p
n_p number of potential defects identified in image p
$\mathbf{z}_a$ feature vector of potential defect a
$\mathbf{x}_a$ position of potential defect a
m number of consecutive frames in which the correspondence will be investigated.

3) Tracking in three views:

k= 0
for i = 1…N_2-1
  for j = i+1…N_2
    if ($B_{i,2}$ = $B_{j,1}$)
      a = $B_{i,1}$; b = $B_{i,2}$; c = $B_{j,2}$
      if trifocal($\mathbf{x}_a$,$\mathbf{x}_b$,$\mathbf{x}_c$)
        k=k+1
        $\mathbf{C}_k$ = [a b c]
N_3 = k

2) Tracking in two views:

k=0
for p = 1…N_1-1
for a = e_p...e_p+n_p-1
  for q = p+1…min(p+m,N_1)
  for b = e_q...e_q+n_q-1
    if bifocal($\mathbf{x}_a$,$\mathbf{x}_b$) and similar($\mathbf{z}_a$,$\mathbf{z}_b$)
      k=k+1
      $\mathbf{B}_k$ = [a b]
N_2 = k

4) Tracking in four views:

k= 0
for i = 1…N_3-1
  for j = i+1…j
    if ($C_{i,2}$=$C_{j,1}$) and ($C_{i,3}$=$C_{j,2}$)
      a = $C_{i,1}$; b = $C_{i,2}$; c = $C_{i,3}$; d = $C_{j,3}$
      k=k+1
      $\mathbf{D}_k$ = [a b c d]
N_4 = k

Figure 5. Tracking algorithm.

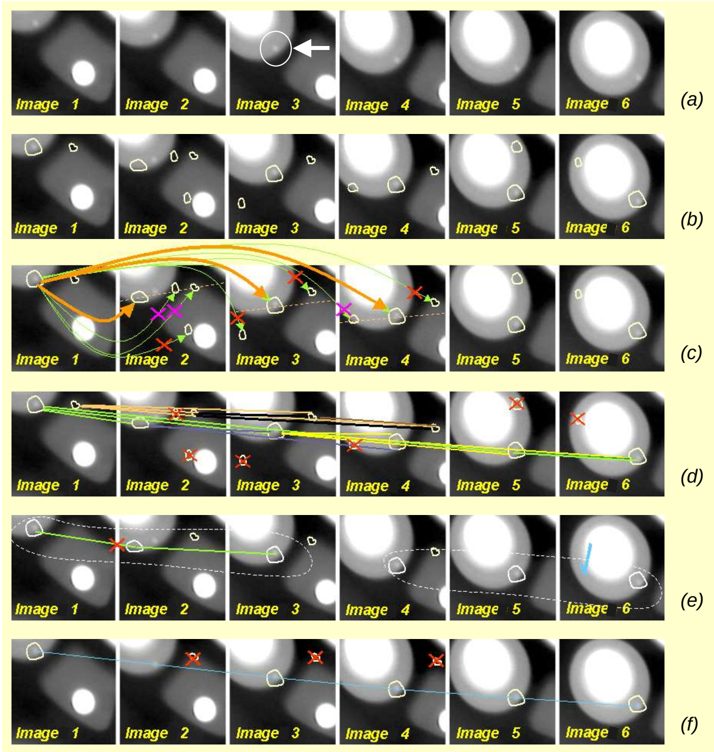

Figure 6. Automated multiple view inspection: a) image sequence with a small discontinuity (see arrow), b) identification of potential discontinuities, c) search of matching in two views, d) remaining potential discontinuities after matching in two views, e) search of triplets, f) tracking in more views, and final detection, the false alarms are eliminated without discriminating the real discontinuities.

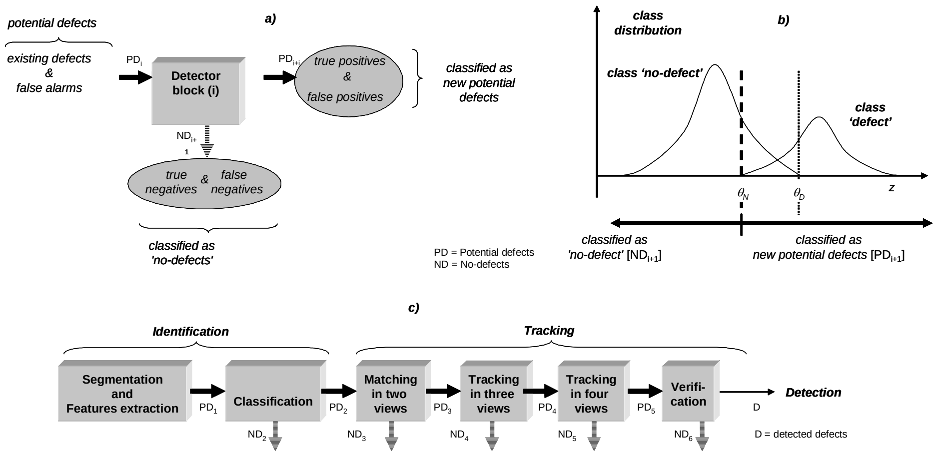

Figure 7. Block diagram of the automated multiple view inspection.

Each step of the automated multiple view inspection can be understood as a detector block, the behavior of which is shown in Fig. 7. The potential defects (PD_i) consisting of existing defects and false alarms are classified as either new potential defects (PD_{i+1}) or no-defects (ND_{i+1}) as shown in Fig. 7a. In a training phase, each detector block is tuned so that the maximal number of false alarms is eliminated from the potential defects without discriminating the existing defects (see θ_N in Fig. 7b). The entire process is illustrated in Fig. 7c. The common strategy is clearly manifested: the detector blocks are configured in cascade, and each detector block eliminates a fraction of the false alarms contained in the potential defects while the existing defects are preserved. The throughput cycle can be considerably incremented if we use an additional decision boundary (see θ_D in Fig. 7b) which guarantee the detection of defects in previous stages without computing the next steps.

We developed two different approaches to estimate the multi-focal tensors required for the tracking algorithm:

i) Calibrated Approach: In[14] we performed the tracking using a calibrated image sequence , *i.e.*, the model 3D $\rightarrow$ 2D was *a-priori* known because it was obtained in an off-line process called calibration.[16] The calibration of an imaging system is the process of estimating the parameters of the model, which is used to determine the projection of the 3D test object into its 2D digital image. This relationship 3D$\rightarrow$2D can be modeled with a transfer function $F: R^3 \rightarrow R^2$. Using this model the multi-focal tensors can be calculated in order to evaluate the multi-focal constraints for the correspondences of the potential defects in the image sequence.[22] The calibration was performed using the well-known photogrammetric calibration,[31] in which a calibration object whose geometry in 3D space is known with high accuracy. Using this technique a true reconstruction of the 3D space without a scale factor is achieved. In the calibration, we estimate the parameters of a geometric model based on n points whose 3D object coordinates $\mathbf{M}_i$ are known, whose 2D image coordinates $\mathbf{w}_i$ are measured, for $i = 1, ..., n$. Using the model we obtain the reprojected points $\mathbf{w}'_i = F(\mathbf{M}_i, \theta)$, *i.e.*, the inferred projections in the digital image computed from the calibration points $\mathbf{M}_i$ and a parameter vector θ. The calibration is performed in each image of the sequence by minimizing the objective function defined as the mean-square discrepancy between measured points $\mathbf{w}_i$ and inferred points $\mathbf{w}'_i$.[22] Usually, the calibration problem is a non-linear optimization problem. In general, the minimization of the objective function has no closed-form solution. For this reason, it must be iteratively minimized starting with an initial guess θ_0 that can be obtained from nominal values or preliminary reference measurements.

ii) Uncalibrated Approach: The calibration is a very difficult task because the iterative estimation of the parameters is very sensible to the initial guess. In addition, the vibrations of the imaging system induce inaccuracies in the estimated parameters of the model, *i.e.*, the calibration is not stable and the computer vision system must be calibrated periodically (off-line) in order to avoid uncertainty. For these reasons, we developed approaches based on the tracking of potential detects in two views[17, 18] and in three views[18] using uncalibrated image sequences, in which it was not necessary to calibrate the imaging system. This new approaches track the potential defects based on a motion model estimated from the image sequence itself. Thus, we obtain a motion model by matching structure points of the test object in the images as shown in Fig. 8. The structure points are matched using B-Spline curves and correlated curve sections of the structure.[17, 18] Using RANSAC[22] the

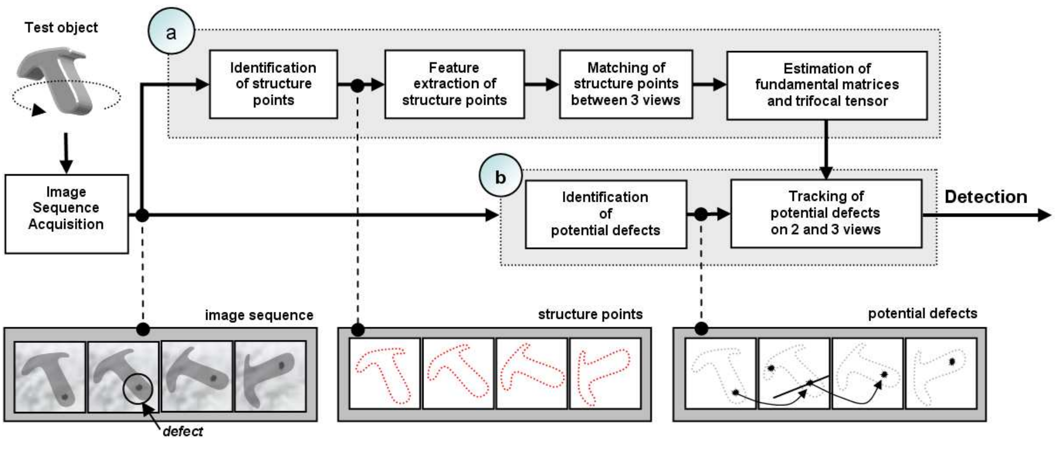

Figure 8. Block diagram of the uncalibrated automated multiple view inspection: a) estimation of motion model, b) detection of defects.[18]

matched structure points are employed to estimated the bifocal and trifocal tensors required for the multiple view analysis. In this sense, we do not calibrate the image sequence, we only estimate the bifocal and trifocal tensors required for the tracking. The great disadvantage of this approach is the inherent difficulty in identification of the structure points (and thus the estimation of the motion model) from the test object itself, when the images of the test object do not significantly differ from each other in the sequence, *e.g.*, a sphere rotating around its vertical axis.

Once the system is calibrated (in the calibration approach) or the motion model is estimated (in the uncalibrated approach) the same algorithm shown in Fig. 5 is used to track the potential defects. The tracking algorithm requires the bifocal and trifocal tensors between the views. In the first approach the tensors are obtained from the projection matrices estimated after the calibration, whereas in the second approach the tensors are obtained using corresponding points of the test object in two and three views.

4. EXPERIMENTAL RESULTS

Several sequences of radioscopic images of aluminum wheels with known flaws were inspected. The sequence of radioscopic images was taken by rotation of the casting at 5^0. Defects were existing blow holes (with $\emptyset = 2.0 \sim 7.5$ mm) and artificial defects produced by drilling small holes ($\emptyset = 2.0 \sim 4.0$ mm) in positions of the casting which were known to be difficult to detect (see some examples in Fig. 9). Table 1 summarizes the results obtained on real data using calibrated and uncalibrated approaches. We calculate the performance of the identification and the performance of the tracking separately. In the table, *true positives* are the number of defects correctly detected and the percentage is calculated related to the number of the existing defects, whereas *false positives* (or false alarms) correspond to the number of 'no-defects' misclassified as 'defects' and the percentage is given related to the number of detected potential defects. We present three implementations of the calibrated approach. They perform the tracking in three, four and five views (cases C-I, C-II and C-III respectively).[14] We observe that the number of false alarms in the identification is enormous. However, the results are perfect for four views (case

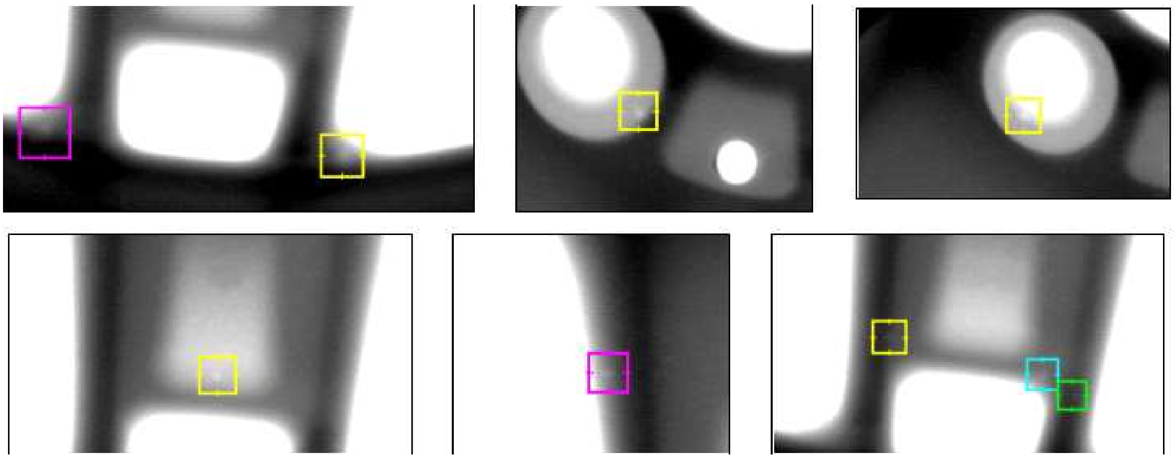

Figure 9. Detection in six images using C-II algorithm.

Table 1. Performance of calibrated and uncalibrated approaches.

					Identification				Tracking			
Method	Name	Analyzed Images	Tracked Views	Existing defects	True Positives		False Positives		True Positives		False Positives	
Calibrated	C-I	72	3	84	71	85%	4310	98%	71	100%	24	25%
	C-II	72	4	84	71	85%	4310	98%	71	100%	0	0%
	C-III	72	5	84	71	85%	4310	98%	59	83%	0	0%
Uncalibrated	U-I	24	2	39	39	100%	83	68%	36	92%	4	10%
	U-II	72	2	233	190	82%	205	52%	190	100%	93	33%
	U-III	72	3	233	172	74%	205	52%	170	99%	19	10%

C-II) where all defects are detected without any false alarms. The verification of the correspondence on three views flags too many false alarms. On the other hand, with 5 views we cannot ensure the segmentation of a defect in five views, for this reason some defects cannot be detected. We increase the performance in the segmentation in the uncalibrated approaches reducing the number of false alarms significantly. In case U-I[17] we perform the tracking in only two views using B-spline curves for the motion model. In case U-II[18] and U-III[18] the tracking is done in two and three views respectively using correlated curve sections of the structure for the motion model. The results of case U-III are promising because all defects to be tracked, *i.e.*, defects that are present in three views, could be tracked, with only a few number of false alarms. We observe that the performance obtained in calibrated approach is higher, however the calibration is in many cases an excessively difficult and unstable task that can be avoided using an uncalibrated approach.

5. CONCLUSIONS

Automated visual inspection remains an open question. Many research directions have been exploited, some very different principles have been adopted and a wide variety of algorithms have been appeared in the literature of automated visual inspection. Although there are several approaches in the last 25 years that have been developed, automated visual inspection systems still suffer from i) detection accuracy, because there is a fundamental trade off between false alarms and miss detections; and ii) strong bottleneck derived from mechanical speed (required to place the test object in the desired positions) and from high computational cost (to determine whether the test object is defective or not). In this sense, Automated Multiple View Inspection offers a robust alternative method that uses redundant views to perform the inspection task. We believe that the method is opening up new possibilities in inspection field by taking into account the useful information about the correspondence between the different views of the test object. Two approaches were developed in the last years: the calibrated and the uncalibrated approaches. Both of them achieve very good performance. However, the calibration of the first approach is a very complicated task, and the identification of structure points in the second approach is inherently difficult when the images of the test object do not significantly differ from each other in the sequence. In order to avoid the mentioned problems, we are working on an on-line calibration of the multiple view system using a calibration object attached to the test object which is imaged in all views. Thus, the images have an enough number of points to calibrate the system.

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