Bimodal Model-based 3D Vision and Defect Detection for Free-form Surface Inspection

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Abstract: This paper presents a 3D vision sensor and its algorithms aiming at automatically detect a large variety of defects in the context of industrial surface inspection of free-form metallic pieces of cars. Photometric stereo (surface normal vectors) and stereo vision (dense 3D point cloud) are combined in order to respectively detect small and large defects. Free-form surfaces introduce natural edges which cannot be discriminated from our defects. In order to handle this problem, a background subtraction via measurement simulation (point cloud and normal vectors) from the CAD model of the object is suggested. This model-based pre-processing consists in subtracting real and simulated data in order to build two complementary "difference" images, one from photometric stereo and one from stereo vision, highlighting respectively small and large defects. These images are processed in parallel by two algorithms, respectively optimized to detect small and large defects and whose results are merged. These algorithms use geometrical information via image segmentation and geometrical filtering in a supervised classification scheme of regions.

1 INTRODUCTION

The context of this article is the industrial surface inspection (defect detection) of free-form metallic car parts. Such a part is shown at the top left of figure 1. Inspection is performed just after the production and is generally done by human experts. This has the drawbacks to be tiring, costly and above all subjective. Many efforts are currently done to automate this process. Comparing to most of the existing automated inspection procedures, the new challenge is to handle free-form surfaces.

Standard industrial cameras and controlled lighting are used in this work. Three examples of defects visualized by a sensor composed of a camera (resolution: 33um/pixel) and one punctual light source are shown on figure 1. Traditionally in industry, feature extraction and classification are applied on images of relatively planar surfaces. Such procedures applied on images of free-form surfaces will lack of reliability because:

1- **Visibility (shading) problem**: because of the free-form of the surface, the visibility of a defect in the image depends too much on the positions of light source and camera.

2- **Background problem**: the free-form of the surface introduces natural edges which cannot be easily discriminated from our "unfeatured" defects.
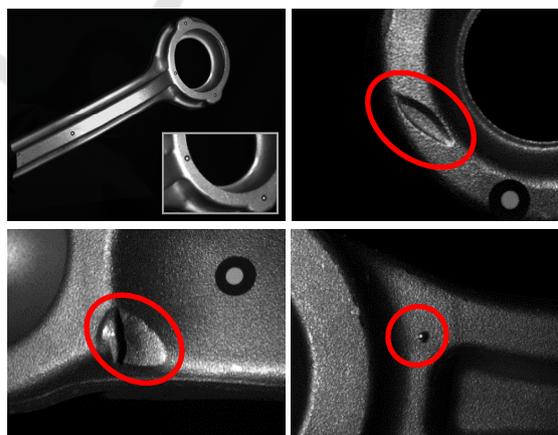

Figure 1: Top-left: free-form mechanical parts of cars. Others: examples of defects of different shape and size.

The first problem discards the direct use of such images as input of the detection algorithm. Because our defects are 3D, a solution is to use 3D vision sensors. We use photometric stereo (building an

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image of surface normal vectors), avoiding the shading problem and enabling the detection of our "small" defects. However, it is only sensitive to the defect depth gradient and its integration lacks of reliability (Ne, 05). This limits the ability to detect some of our flat "large" defects, such as the one at the top right of figure 1. To overcome this problem, an active stereo vision system (building a dense 3D point cloud) is also used.

The second problem occurs whatever the data used, and thus a pre-processing has to be done. Some methods currently applied on images could be applied on 3D data. Thus they are presented below although only 3D data are used in our work. There are two approaches suggested in the literature to solve the second problem: restoration and background subtraction.

Restoration: it filters the undesired elements. It is used in inspection of textile, wood and metallic surfaces to remove structural/statistical textures (Ts, 01) (Ts, 03), or repetitive patterns (He, 05) in which the defect is embedded. Morphological filters are also used to highlight defects of specific shapes (Zh, 02). However, natural edges have no specific features and cannot be discriminated from our defects, thus they cannot be filtered.

Background subtraction (applied on images and 3D data): it consists of building a (monochrome) "difference" image (input of the classification algorithm) by subtracting a reference data set (our "background" is the data without defect) from the real data set. In the difference image, the defect generally contrasts in radiometry with the background. In the context of change or motion detection in images, the reference data set is often an image of the same scene taken previously. In our context it has to be built. In (Ch, 16), the theory of sparse representation and dictionary learning is used in the case of images. This approach generates a "flexible" reference image, adjusted to the uncertainties (localization, illumination, texture and geometric tolerances of the part) of its corresponding real image. The success of the method depends on the reliability of the decomposition models and on the quality of the dictionary, which is generally learned (Lu, 13). However, the method has not been yet extended to 3D data, and this is why we do not use it in this work.

Another technic to obtain a reference data set is to simulate the data from the CAD object model. To perform that, we have developed a simulator enabling to work in a 3D virtual space containing the CAD and the sensor model. The sensor model can be moved with respect to the CAD, and sensor data

can be simulated from a chosen viewpoint. In our application, once the real sensor is localized with respect to the object, the sensor model is positioned accordingly in the virtual space in order to obtain simulated data registered with the real data. This model-based approach generates a "perfect" reference data set, but not a "flexible" one like with a dictionary. However, it has the great advantage to be easily used with 3D data, and this is why we use it in this work. In our context of image-based defect detection, the CAD model is currently not very used in industry, and when it is used it is generally without data simulation.

In this work two 3D vision sensors are used (for large and small defects). For each one, a model-based background subtraction generates a difference image. The independent and complementary "photogrammetric" and "photometric" difference images are the input of the classification algorithm (see figure 2). Figure 3 shows the hardware of the system. (Ne, 05) suggests a rendering technic building an "improved" 3D point cloud by combining a measured 3D point cloud and a surface normal vector image. Data merging presenting a risk of loss of information, it is not retained in this work.
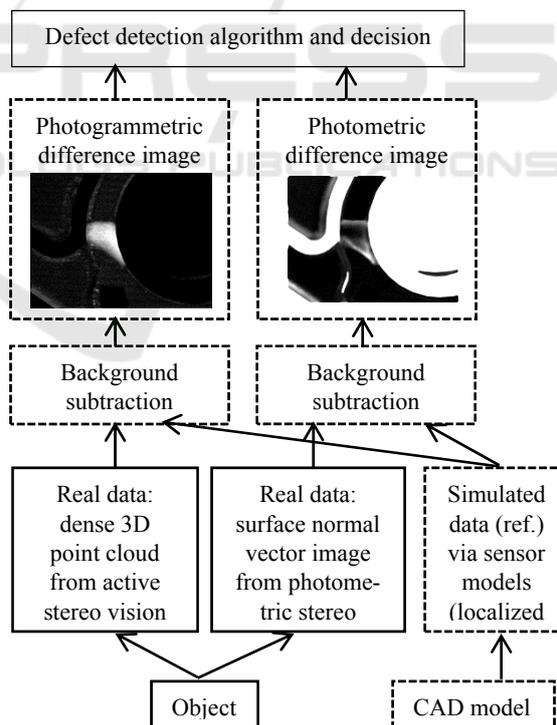

Figure 2: Flow diagram of the defect detection system: 3D vision sensor combination (solid boxes), background subtraction via simulation from the CAD model (dotted boxes), and finally feature extraction, classification, merging and decision algorithm.
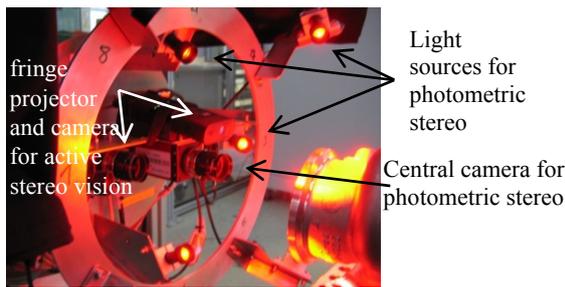
Figure 3: Hardware of the vision system (fully-calibrated).

The sensors and their ability to visualize defects in their difference images are explicated in part 2. The classification algorithm (and related works) is detailed in part 3. The classification results are in part 4 and part 5 is the conclusion.

2 SENSORS & VISUALIZATION

This section presents our two 3D vision sensors and shows their complementarity and ability to visualize defects in their difference images. The first sensor uses photometry to visualize small defects (their gradients are visualized), while the second uses photogrammetry for visualizing large defects.

2.1 Photometry

The resolution of our camera is 33um/pixel, enabling to visualize our small defects, which can be as small as 0.3mm². Photometric stereo (building an image of surface normal vectors) provides a difference image of this resolution while avoiding shading effect. The difference image visualizes the defect depth gradient.

Photometric stereo consists in reconstructing the surface normal vectors from N images ($N \geq 3$) having different illuminations. Let us consider the case of a perfectly diffuse surface (Lambertian reflectance model). For each pixel we have N brightness equations: $\{I_i = I_{0i}\rho v_i . n\}$ with $1 \leq i \leq N$. $\{I_i\}$ are the measured pixel intensities. $\{v_i\}$ and $\{I_{0i}\}$ are the (generally known) light source directions (vectors) and intensities. n is the (normalized) surface normal vector and ρ is the surface albedo (generally unknown). Thus we have N non-linear equations and three unknowns. This system has a closed-form solution. See (He, 11) for generalization.

Photometric stereo in our work and contributions: our sensor contains eight distant and punctual light sources (figure 3). We assume that our surface

reflectance has diffuse and specular components. Also, our free-form surface and the 3D defects produce shadows in the images. Thus, the ith intensity of a pixel in our sequence is not systematically close to $I_{0i}\rho v_i . n$ (Lambertian model), but can be clearer due to specularity or darker due to shadow. We discard these outliers using the method of (Br, 12) and then estimate the normalized surface normal vector and the albedo from (at least three) inliers via least squares. Our contribution is that we overcome the problem of the limited dynamic range in intensity of the camera. For each illumination, a robust high dynamic range (HDR) image is computed from five acquisitions with different exposure times (He, 14).

Our photometric stereo sensor provides a "color" image containing the normalized surface normal vectors (see figure 4.1, figure 6.1 is the raw image). The difference image is formed with the Euclidian distances between these real vectors and their corresponding simulated ones (simulation in figure 4.2; difference image in figure 4.3). The intensity of this image is related to the absolute value of the defect depth gradient. Figure 5.1 shows a zoom of a small defect (kind of dome). Without surprise, its depth gradient is visible in the difference image (figure 5.2). Photometric stereo is a gradient measurement, and it is difficult to reconstruct the defect depth by integration. Thus this approach has difficulties to visualize properly large defects having flat surfaces (missing material). An example is shown on figure 4.3 (raw image on figure 6.1). To overcome this problem, stereo vision is combined with photometric stereo (part 2.2).
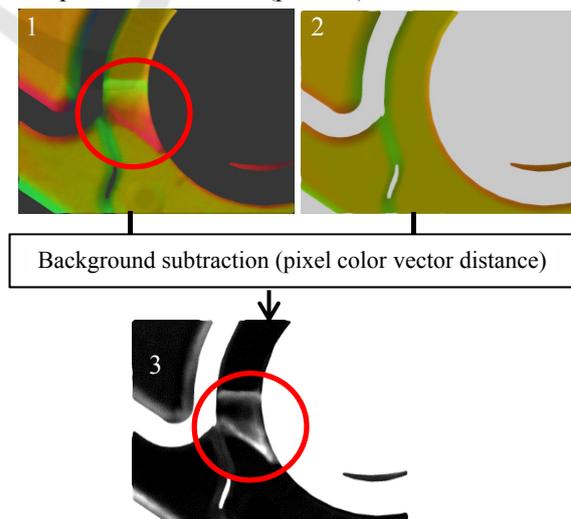

Figure 4: 1: Real (normalized) surface normal vector image. 2: Simulated data. 3: "Photometric" difference image (defect depth gradient are visible).
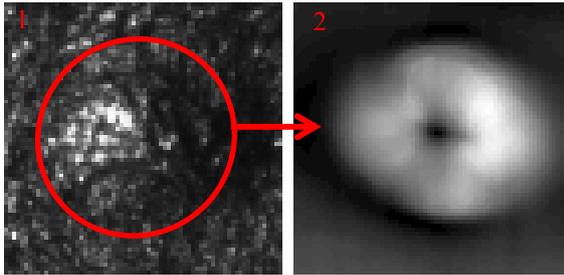
Figure 5: 1: Zoom of a small defect such as the one at the bottom right of figure 1 (dome of area 0.8mm²). 2: "Photometric" difference image.

2.2 Photogrammetry

Because photometric stereo is limited to visualize large defects, this part introduces an active stereo vision system (producing a dense 3D point cloud) enabling their suitable visualization. The difference image is formed with the Euclidian distances between the real 3D points and their closest simulated ones. The intensity of this image is related to the absolute value of the defect depth. Without surprise, large and deep defects are very visible with photogrammetry (see figure 6.2; figure 6.1 is the raw image), and the visibility is much better than with photometry (compare figure 6.2 with figure 4.3). The resolution of the "photogrammetric" difference image is only of 0.9mm² (triangulation-based methods generally provide a resolution loss (He, 11)). In fact, our stereo vision system cannot visualize our smallest defects (figures 6.4). This is not important because the photometric stereo system handles the small defects (figure 5.2), but shows the complementarity of the two systems.
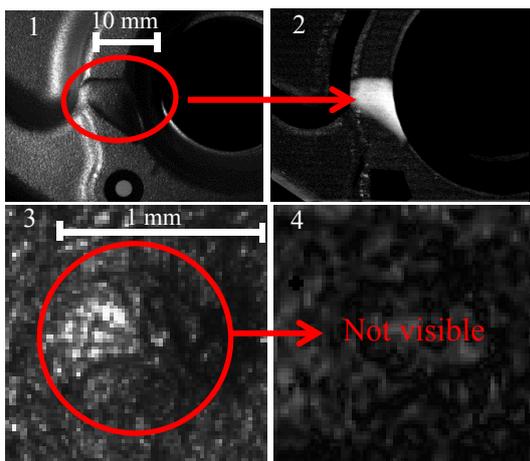

Figure 6: 1: a large defect, 3: same as figure 5.1. 2 and 4: "photogrammetric" difference images.

3 DETECTION ALGORITHMS

Automated and reliable defect detection algorithms for the inspection of mechanical parts are more and more needed in industry. Section 3.1 briefly presents the main classification technics in image processing, and positions our work with respect to them. Section 3.2 describes our defect detection algorithm.

3.1 Brief Background and Position of our Method

Some detection algorithms are directly applied to 3D measured data (Th, 15). However in the following only image classification is considered, because our detection algorithm has images in input (the monochrome difference images). A classification approach is characterized by the entities it considers (pixels or objects), the feature extraction and the classifier itself.

Whatever the context, the most used approach is by far the classification of pixel features (intensity, RGB vector …) (Lu, 14) (Ts, 03) (Zh, 02) and (Ch, 16). This approach is used in the article (Li, 07) using the Torrance and Sparrow surface reflectance model parameters (computed from photometric stereo) as pixel features. However, with this technic each pixel is processed individually without considering its spatial context in the image (no overall regularization). Pixel-wise classification is not used in our work because it can provide a relative instability (our defects are objects, not pixels) and does not use any spatial information. Approaches based on hidden Markov random fields exploit spatial information (Sc, 09). The problem is that they require initialization and are time consuming when large images are processed.

Image segmentation avoids the previous drawbacks and uses contextual information in order to group pixels into objects (regions) (Ta, 10) (De, 09). In our work, a segmentation algorithm is applied on the input image (a defect region should contain at least one segmented object). Once image segmentation is performed, two strategies can be used for the classification.

The first is a pixel spectral classification and to assign to a segmented object the predominant pixel class within it (majority vote) (Li, 07). This method does not use geometry, thus it is adequate when the defects have few specific geometry or e.g. to detect forests in aerial rural images.

The second is to design and classify a pattern for the segmented object. When the defects have few specific geometry (or in natural environment), the

components of the pattern are generally only spectral (Li, 07). In man-made environment, classes of interest often have specific geometry (size, shape) and in that case the pattern can possibly have spectral and spatial components. For example, in order to detect road and building in color (RGB) aerial urban images, the article (Si, 11) forms a pattern whose components are the mean RGB vector over the segmented object (spectral), the area and the eccentricity (spatial). The use of geometrical features has improved the class separability and thus the classification accuracy.

In our work the above second strategy is retained. However, our defect class has not enough geometric features to integrate spatial components into the pattern. In contrast, the defects (or their gradients) are generally clearer than the background in the difference images (figure 2). Thus, spectral components such as the mean intensity value can be retained. Although (in our work) geometry cannot be used to form pattern components, it can be exploited in a soft manner just after the segmentation (especially for our small defects) in order to decrease the risk of false positives. If our defect class has a geometric feature inside a range, segmented objects outside this range are eliminated. We call this operation the geometrical filter.

Supervised classification methods (Bi, 07) and combination of different approaches are intensively used to detect defects. For example, the article (Su, 08) combines neural network (NN) and fuzzy logic in order to train a 6-class classifier. In this article, object-based feature extraction is implicit because the input image contains only the inspected part on a perfectly dark background. In the context of road and building extraction in color aerial urban images, (Si, 10) combines a "3 class" support vector machine (SVM) classifier with a single class SVM in order to improve the classification accuracy.

In our work, the classification is supervised (via a training set). However, sophisticated supervised classification schemes such as NN or SVM are not needed because our pattern has only one (spectral) component and we have only two classes (defect or not). Instead, during the learning the threshold is manually fixed using a training set.

3.2 Our Detection Approach

Figure 7 shows that the two difference images are processed in parallel by the algorithms *algo3D* and *algoN*, optimized to detect large and small defects and the results merged with a logical "or".
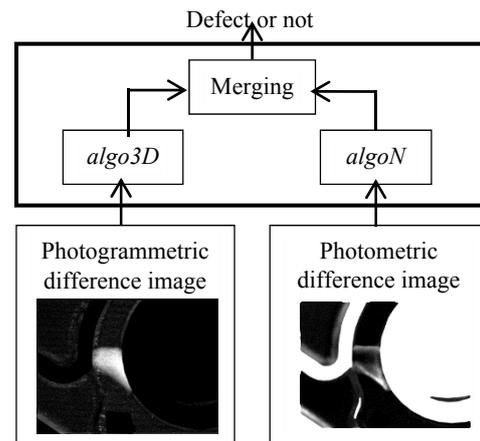

Figure: 7: Defect detection algorithm and decision.

Algorithms *algo3D* and *algoN* have the same structure as discussed in the previous section. The input image is first segmented (object approach), then a geometrical filter is applied to discard improbable regions (against false positives). Afterwards, a one dimensional radiometric pattern is computed for each (remaining) segmented object. Pattern classification is performed via a threshold which was manually fixed using a training set (supervised classification). It has been noticed that when a defect area is larger than 5mm² photogrammetry should be used, else photometry is more reliable. Thus 5mm² is the border between large and small defects.

3.2.1 algo3D

This algorithm, described on figure 8, is designed to detect large defects (from 5 to 200mm²). These defects have no shape feature, thus the geometrical filter only discards segmented regions smaller than 0.9mm² (system resolution). The lower limit is largely smaller than 5mm² because a segmented region on the defect can be smaller than the defect.

A large defect has generally a depth upper than 0.3mm. A threshold of this value is applied on the difference image, enabling to form a pattern invariant with respect to the defect depth: the number of white pixels in a segmented region divided by the region area. It also generally discards almost all the small aggregates produced by the imperfections of the fringe projector (see figure 10, left column). The morphological dilatation makes more compact the large defect regions (suppression of the holes), while the erosion limits the risk of false positives by eliminating the possible remaining bright (above the threshold) small aggregates.

The lower limit of the geometrical filter enables the detection of small defects which are larger than 0.9 mm²; however the morphological erosion reduces this ability. In fact, *Algo3D* can detect some small defects but is not optimized for that. In this case *algoN* is more performant to detect them.
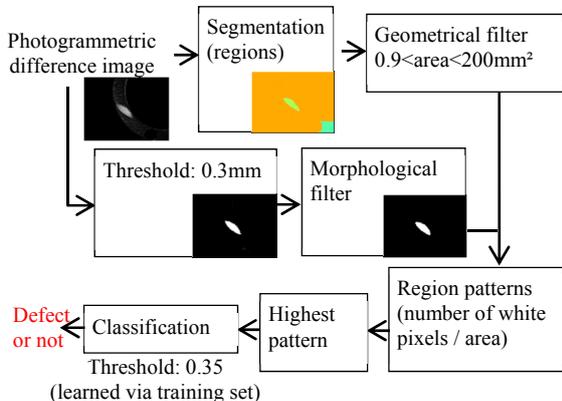

Figure 8: *algo3D*: large defect detection from the photogrammetric difference image.

3.2.2 algoN

This algorithm, described on figure 9, is designed to detect small defects (from 0.3 to 5mm²). It is the defect's gradients which are visible in the photometric difference image, thus it is these regions (or part of them) which can be detected instead of the defect directly. Our small defects have rough shape features, and thus also the segmented regions lying on their gradients. They are never extremely elongated and have no chaotic border. More precisely, their areas, eccentricities, compactness and concavities are inside some ranges (see the geometrical filter in figure 9).

A Canny edge detector is applied to the difference image to form a pattern invariant to the defect depth: the percentage of edges in a segmented region (notably defect's gradient regions).
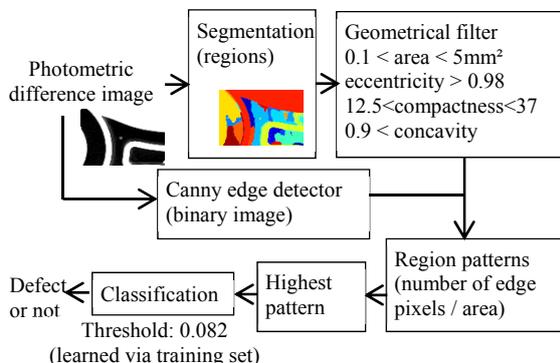

Figure 9: *algoN*: small defect detection from the photometric difference image.

4 RESULTS

4.1 Qualitative Results

Figures 10, 11 and 12 show large and small defects respectively detected by *algo3D* and *algoN*. The difference image is at the left, the defect is shown at the right and the segmented region of the highest pattern (classified here as defect) is marked in red.

Sometimes the segmented region is spread over the entire defect (or defect's gradient), and sometimes only on a part of it. This mainly happens when the defect has strong depth only on a part of it (and also only the segmented region of the highest pattern is visualized, while possibly some others are on the defect region and are classified as defect). The two cases are equivalent because our aim is the detection, not the accurate extraction. Among these examples, no defect has been detected by both *algo3D* and *algoN* (complementarity).
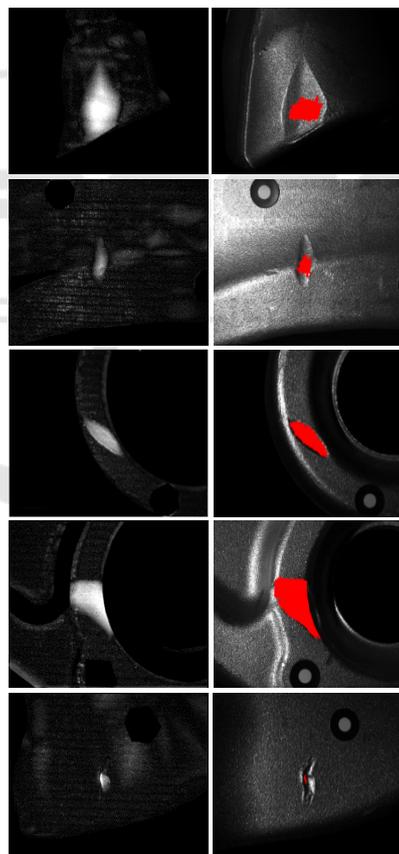

Figure 10: Large defects detected by *algo3D*. Left: photogrammetric difference image. Right: the segmented region of the highest pattern (classified as defect) is in red on the raw image.
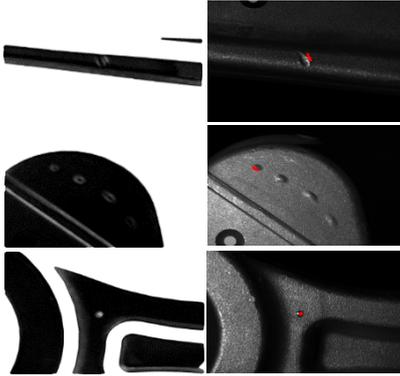
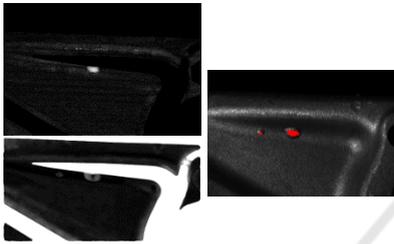Figure 11: Small defects detected by *algoN*. Left: photometric difference image. Right: like in figure 10.

Figure 12: Large and small defects respectively detected by algo3D and algoN. Left: the photogrammetric (top) and the photometric (bottom) difference images. Right: like in figure 10.

4.2 Quantitative Results

Three hundred and sixty five acquisitions are used for the test. This set includes one hundred and sixty positives (containing at least one defect), with the same overall quantity of large and small defects. Consider *algo3D* (or equivalently *algoN*), the highest pattern and its segmented region:

If the real class is positive: if the segmented region is on the defect region and the pattern is classified as positive, we have a true positive (TP). If the pattern is classified as negative, we have a false negative (FN). If the segmented region is outside the defect region and the pattern is classified as positive, we have a false positive (called FP2).

If the real class is negative: if the pattern is classified as positive, we have a false positive (called FP1). If the pattern is classified as negative, we have a true negative (TN).

The overall accuracy (% of correct classification) is: $100 \times (TP + TN)/(TP + TN + FP1 + FP2 + FN)$. The results of each method are reported in table 1.

Table 1: Results of the algorithms.

	algo3D	algoN	**Merging**
TP	112	48	**133**
TN	205	200	**200**
FP1	0	5	**5**
FP2	6	7	**6**
FN	42	105	**21**
Overall accuracy (%)	86.8	67.9	91.2

algo3D provides good results (table 1). As expected, it detects almost systematically the large defects (>5mm²), and also sometimes smaller defects. Its forty two FN are mainly small defects. The results of *algoN* are less good. This was expected because it is designed to detect only small defects. Sometimes large defects are detected via the detection of parts of them. More than 80% of the small defects are detected, this is better than with *algo3D*. The combination of these complementary algorithms significantly improves the overall accuracy with respect to *algo3D*. *algoN* is very useful because it detects twenty one (generally small) defects that *algo3D* not detects. Only twenty seven TP are detected by both *algo3D* and *algoN*. This confirms their high complementarity.

FP1 and FP2 are due to higher measurement error at natural edges. These errors are often visible in the difference images and sometimes detected, particularly with *algoN* due to its higher sensitivity. FN are the main problem because more numerous. They occur mainly with small defects (*algoN*). Generally, the segmentation extracts them suitably (more exactly parts of their gradients are extracted), thus the problem is a too low pattern. It happens when the edges of the defect's gradient are mainly outside the segmented regions or when the defect is not visible enough due to low depth gradient (too few edges extracted).

5 CONCLUSION

A model based vision sensor and defect detection algorithm combining stereo vision and photometric stereo were presented. Measurement simulations via the CAD model enabled to build two complementary difference images. One visualizes well large defect depths, making possible the detection of large defects. The other makes visible small defect depth gradients, enabling the detection of small defects. The combination of the results of the two complementary detectors enables to obtain an overall accuracy of 91.2%. A future challenge is to

reduce measurement error at natural edges (FPs). FNs occur mainly with small defects and are generally due to a low pattern. A second version of *algoN* configured to detect defects having low depth gradient could be tested. With this third class of defects, the geometrical filter range for the area could be from 0.1 to 2mm². The segmented regions of the defects (or more exactly of parts of the defect gradients) are relatively elliptic, thus an additional shape feature "fit with an ellipse" could be included in the geometrical filter or maybe even integrated as spatial component into the pattern. The spectral component of the pattern should be maintained because other segmented regions are elliptic. To have a higher spectral component, the Canny edge detector should be much more sensitive.

The prototype will be completed to perform an automatic inspection of the entire object via model-based sensor planning (Ch, 11) and motion planning (La, 06) technics. A robot arm will move the object between two successive acquisitions. In the virtual space, measurements will be simulated from each computed viewpoint. Then during the plan execution in the real world, real measurements will be done from these viewpoints. Once the entire object is captured, the defect detection processing can be applied in parallel to the data of each viewpoint.

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