# A Probabilistic Approach for Defect Detection based on Saliency Mechanisms

Francisco Bonnin-Pascual and Alberto Ortiz
Department of Mathematics and Computer Science
University of the Balearic Islands
07122 Palma de Mallorca, Spain
{xisco.bonnin, alberto.ortiz}@uib.es

***Abstract*—The use of saliency mechanisms for defect detection is discussed in this work. We consider defects on regular surfaces as conspicuous areas that catch the attention of the surveyors. Following this approach, we propose the use of the Bayesian framework SUN, devised to provide saliency information based on natural statistics, to combine information about the visual appearance of the surface under inspection, to finally indicate where the defects (if any) are located. The visual information is suggested to be based on features commonly used to predict human eye fixations: contrast and symmetry. We demonstrate that these two features provide a description of the surface that can be used to indicate whether it is defective or not. Our approach is assessed using a publicly available image dataset containing a variety of surfaces with defective areas. The performance of the defect detector is evaluated through cross-validation and successful results are obtained.**

## I. Introduction

Defect inspection is a task typically required in manufacturing processes (from tiles to integrated circuits) and the maintenance of installations (buildings, industrial plants, ships , aircrafts...). During such inspections, defects that can compromise the usefulness of the product or the integrity and safety of the installation are supposed to be detected. Computer vision has been used on many occasions for automated and semiautomated defect detection using images as input. Following this approach, many methods can be found in the literature for detecting different kinds of defects. By way of example, [1] succinctly overviews some of them.

Saliency mechanisms have been successfully used in a number of applications including prediction of human eye fixations, image segmentation, object recognition, image retargeting, thumbnailing and retrieval [2], [3]. Almost all attentional models are inspired by cognitive concepts and intend to emulate the human vision system in order to pay more attention to certain areas of the image, those that humans consider that contain more important information.

This paper introduces the idea of using saliency mechanisms for defect detection. We consider defects as anomalous situations that draw the attention of the inspector. Note that this approach is less restrictive than looking for a specific defect characterized by a certain set of visual features. In the literature we can find some examples of using saliency to detect specific defective situations on specific materials or components (on LCD panels [4], on paper [5], etc).

More precisely, our approach consists in using saliency information provided by the Bayesian framework SUN [6] to indicate where defective areas (if any) are situated. We use this framework to combine visual information for computing the probability of being defective at every image point. This probability is computed relying on the experience learned in advance from a collection of images, instead of just relying on the information obtained from the image under inspection.

To feed this Bayesian framework, we use features commonly employed for predicting human eye fixations. The rationale behind this idea is that we consider defects as something that catches the visual attention of surveyors during visual inspection. We propose to use two different features:

- on the one hand, contrast in luminance, color and orientation as defined in the saliency model by Itti et al. [7], which has become one of the most influential saliency models;
- on the other hand, symmetry as defined in the saliency model by Kootstra et al. [8], which has proved to outperform previous models when the goal is to predict human eye fixations.

These two features supply complementary information about the image elements, and the experiments performed in this study indicate that they are suitable for guiding defect inspection processes.

## II. A Bayesian Approach for Defect Detection

We consider defects as rare phenomena that may appear on a regular surface or structure. Since they are rare, the probability of an area of being affected by some kind of defect is rather low. In this paper, we propose to use this low probability to indicate salient areas in digital images, that we expect to coincide with defects.

A similar idea, but applied to the detection of general targets, is used by Zhang et al. [6]. In their paper they propose a Bayesian framework that incorporates top-down information with bottom-up saliency (self-information of visual features) to provide the pointwise mutual information between the features and the target, when searching for a target. They call their framework *Saliency Using Natural Statistics* (SUN) since they focus on learned statistics from natural scenes.

In our approach, we compute the probability of different features suitable for describing defective areas and combine them using the SUN framework. In the original framework, saliency at a given point $z$ is defined as:

$$S_z = \underbrace{\frac{1}{p(F=f_z)}}_{\substack{\text{Independent}\\ \text{of target}\\ \text{(bottom-up saliency)}}} \underbrace{\underbrace{p(F=f_z|C=1)}_{\text{Likelihood}}\underbrace{p(C=1|L=l_z)}_{\text{Location prior}}}_{\substack{\text{Dependent on target}\\ \text{(top-down knowledge)}}} \tag{1}$$

where $F$ consists of the visual features of a point, $f_z$ represents the feature values observed at $z$, $L$ is the location (pixel coordinates) of a point, $l_z$ represent the location of $z$, and $C$ denotes whether a point belongs to a target class or not ($1$ = target class).

Since defects do not depend on their location on the image, the formulation can be simplified:

$$S_z = \frac{1}{p(F=f_z)} p(F=f_z|C=1) \tag{2}$$

Using this formulation, the saliency of a given point $z$ decreases as the probability of features $f_z$ is higher, and increases as the probability of $f_z$ in defects increases. To estimate these probabilities, the Parzen windows method [9] has been applied to the histograms obtained for the different features computed for all the images of a training set (further explained in Section IV). This training step entails an additional advantage: saliency is not only based on the features observed on the image under inspection but on the statistics obtained in advance from a learning set of images.

The selection of the features used to feed the Bayesian framework as well as their suitability for describing defects is explained in Section III.

## III. Defects and Salient Features

During a visual inspection process, defects –considered as rare phenomena– will potentially attract the visual attention of the surveyor. Following this idea, we propose to describe defects using features typically used in cognitive models to predict human eye fixations.

Among them, we focus on those which can be evaluated through a saliency map. A saliency map consists in a topographic map that represents the conspicuousness of the different areas of the input image [10]. This is typically shown as a gray-scale image where locations with higher conspicuity values are closer to white and less salient areas are closer to black.

One of the most influential saliency computational approach following a model-based paradigm is based on contrast [7]. This model was presented in 1998 by Itti et al. and it is inspired by the behaviour and neuronal architecture of the early primate visual system. It computes multi-scale center-surround differences in intensity, color and orientation spaces, resulting in three conspicuity maps that are combined to obtain the final saliency map. Contrast obtained through Itti's model is the first feature that we consider to describe defects.

The second feature that we propose is symmetry. This is computed through the isotropic operator proposed by Koostra et al. [8]. This operator has been successfully used for predicting human eye fixations in complex photographic images where symmetry is not so evident. Furthermore, its authors use the contrast model by Itti et al. as a reference for comparison. The results show that, on many occasions, the symmetry operator outperforms the contrast one.

The suitability of using contrast and symmetry when looking for defects has been checked after computing the levels of both features in images from our dataset (further described in the next section). Figure 1 shows a test image together with its ground truth (defective areas are labelled in white) and the contrast and symmetry maps obtained using the aforementioned methods. As can be observed, all the defective areas in the image concentrate higher values of contrast and symmetry while non-defective areas result darker, since they obtain lower values for these two metrics. The same behaviour is observed with the rest of the images in the dataset.

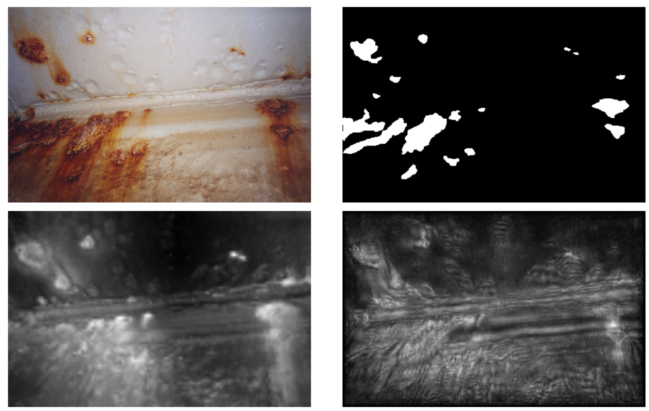

Figure 1. Contrast and symmetry levels on defects. From left to right and from top to down: test image, ground truth, contrast map and symmetry map. In the feature maps, lighter pixels indicate higher values.

## IV. Assessment of the Defect Detector

In this study we have used a dataset with 73 images of large surfaces and structures including defective areas (cracks, coating breakdown and different kinds of corrosion). This dataset is available online[1] and also includes the ground truth, consisting in black and white images where defects are labelled in white (see top right image in Fig. 1).

SUN requires from a training step where different probability density functions must be computed. In our case, both contrast and symmetry PDFs have been computed twice: once for all the pixels of the images of the training set and once again just for those pixels labelled as defective in the corresponding ground truth image. The learning process therefore provides four PDFs.

Figure 2 shows, by way of example, the four PDFS obtained for the entire dataset. The contrast and symmetry values have been normalized between 0 and 100 to facilitate the comparison. From these plots we can draw some conclusions:

- The majority of pixels present low values of contrast and symmetry (peaks of both continuous lines are slightly above 10) while defective pixels tend to present higher values of both features (around 25 for symmetry and around 35 for contrast).

[1]http://dmi.uib.es/~xbonnin/resources

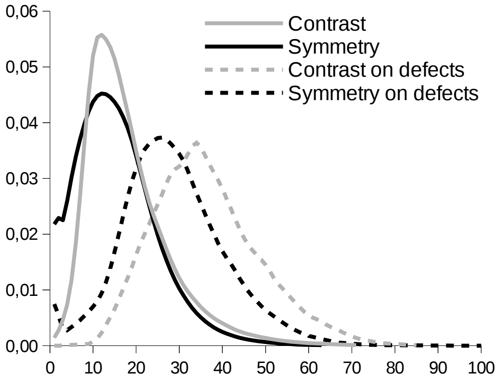


Figure 2. PDFs obtained for contrast and symmetry features. Dashed plots represent the values obtained when just considering pixels on defective areas.

- Contrast peaks are farther from each other than symmetry peaks. This could indicate that contrast will perform better than symmetry when classifying pixels as defective or non-defective. In other words, contrast seems to be more discriminative than symmetry when describing defective areas.

To evaluate the contribution of each feature to the performance of the defect detector, the assessment has been performed in three stages: first using just contrast, secondly using symmetry alone and finally using both features together. In other words, this section compares the results obtained with three different versions of the defect detector.

The performance has been evaluated using Leave-One-Out Cross-Validation (LOOCV) [11]. Following this scheme, one image is selected from the dataset and reserved, while the rest of the images is used to obtain the feature PDFs that make up the defect detector (training step). Finally, the reserved image is used to validate the detector. This process is repeated for each one of the images in the dataset and the results obtained in each iteration are averaged.

Figure 4 presents some classification results for the three versions of the defect detector. These results are provided as gray scale images that we call *defect maps*. In these maps, lighter areas correspond to those pixels for which the detector output suggests higher probability of being affected by some kind of defect. To facilitate the visualization, each map is scaled between 0 and 255 to obtain a full range gray scale image. As can be seen, the three versions of the defect detector tend to assign higher probabilities to the areas that are indeed labelled as defective in the corresponding ground truth image.

To compare the performance of the different versions of the defect detector, a threshold $\tau$ is used to set the pixels which are classified as defective.

In order to perform a quantitative evaluation, we have computed the True Positive Rate (TPR), or sensitivity, and the False Positive Rate (FPR), or fall-out, for the three versions of the defect detector. These have been computed for different values of the threshold $\tau$ to obtain the corresponding ROC curves, which are presented in Fig. 3. Furthermore, to complete the assessment, the values for the Area Under Curve (AUC)

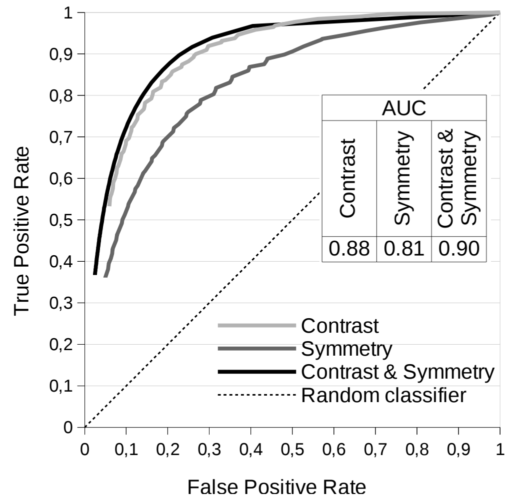


Figure 3. ROC curves and AUC values obtained for the three versions of the defect detector.

[12] have been computed for the tree ROC curves, obtaining the values also presented in Fig. 3.

Comparing the different ROC curves and AUC values we can state some interesting results:

- The three versions of the defect detector present good performances during the classification task: on the one hand, their ROC curves are above the diagonal, what represents good classification results (better than random) and relatively close to the (0,1) corner of the ROC space, which corresponds to perfect classification; on the other hand, the AUC attains a high value above 0.8 for all curves.

- As we have predicted, contrast performs better than symmetry for the dataset employed in this study. This suggests that contrast provides more information to discriminate between defective and non-defective areas.

- The combination of symmetry and contrast results in a defect detector with better performance than the other versions, presenting the highest AUC value (slightly above 0.9). This indicates that symmetry provides complementary information to contrast.

In the light of these results, we can state that the presented framework can successfully detect defective areas in digital images.

## V. CONCLUSION

In this work, we present the idea of using saliency mechanisms for defect detection. We propose to use the Bayesian framework SUN, devised to provide saliency information based on natural statistics, to combine probabilistic information obtained using two different features: contrast and symmetry. These two features have been selected due to their well-known relation with the idea of conspicuity. After some experiments, we prove that contrast and symmetry appear in defective areas with higher probability than in non-defective areas.

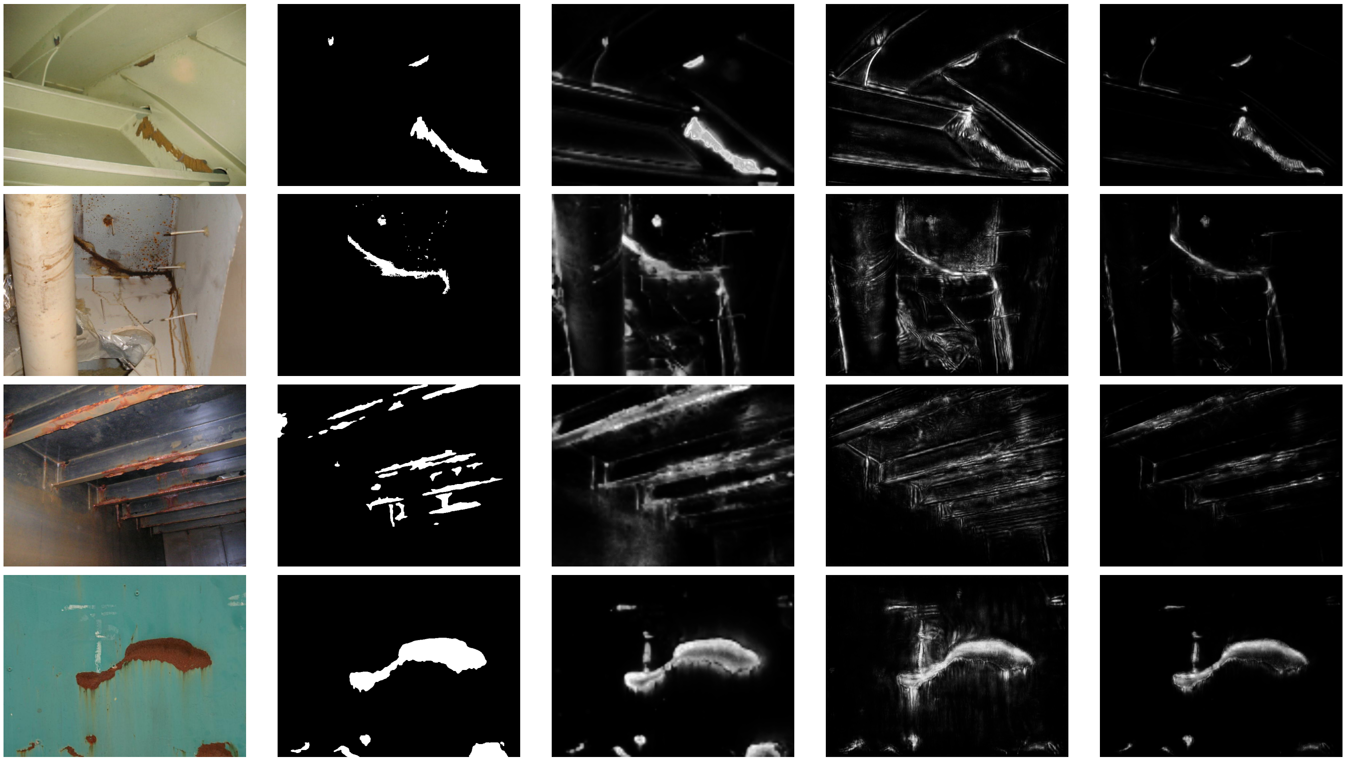

Figure 4. Defect maps obtained for four test images. Columns from left to right: test image, ground truth and defect maps obtained using contrast, symmetry and both features together. In the defect maps, lighter pixels indicate higher probability of being defective.

The Bayesian framework SUN has been fed with information provided just by contrast, just by symmetry and by both features together; resulting in three different versions of the defect detector. After assessing their performances using LOOCV, the results obtained prove the feasibility of using such framework for defect detection in real images.

As future work, we plan to combine specific information describing the kind of defects to be found. For example, corrosion inspection on steel surfaces could be carried out adding roughness and colour information to the Bayesian framework since corroded steel surfaces usually present a rough texture and reddish colours. The usability of these features for corrosion detection have already been proved in [13] and [14]. We plan to estimate the PDFs corresponding to these additional features and combine them with the contrast and symmetry PDFs used in this work. The idea is to test the improvement achieved when adding specific (dependent of target defect) to generic information (based on the conspicuity concept).

## ACKNOWLEDGMENT

This work is supported by the European Social Fund through grant FPI10-43175042V (Conselleria d'Educacio, Cultura i Universitats, Govern de les Illes Balears) and by the FP7 project INCASS (MOVE/FP7/605200/INCASS).

## REFERENCES


[1] F. Bonnin-Pascual, "Detection of cracks and corrosion for automated vessels visual inspection," Master's thesis, University of Balearic Islands, 2010, http://srv.uib.es/ref/1233.html.

[2] Q. Wang, P. Yan, Y. Yuan, and X. Li, "Multi-spectral saliency detection," *PRL*, vol. 34, no. 1, pp. 34 – 41, 2013.

[3] A. Borji and L. Itti, "State-of-the-art in visual attention modeling," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 1, pp. 185–207, jan. 2013.

[4] K.-B. Lee, M.-S. Ko, J.-J. Lee, T.-M. Koo, and K.-H. Park, "Defect detection method for tft-lcd panel based on saliency map model," in *IEEE Region 10 Conference*, vol. A, 2004, pp. 223–226 Vol. 1.

[5] J. Ping and G. Tao, "Paper defects detection via visual attention mechanism," in *Chinese Control Conference*, 2011, pp. 5852–5856.

[6] L. Zhang, M. H. Tong, T. K. Marks, H. Shan, and G. W. Cottrell, "SUN: A bayesian framework for saliency using natural statistics," *Journal of Vision*, vol. 8, no. 7, pp. 1–20, 2008.

[7] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 11, pp. 1254 –1259, nov 1998.

[8] G. Kootstra, A. Nederveen, and B. D. Boer, "Paying attention to symmetry," in *British Machine Vision Conference*. BMVA Press, 2008, pp. 111.1–111.10.

[9] S. Theodoridis and K. Koutroumbas, *Pattern Recognition, 3rd Edition*. Academic Press, 2006.

[10] C. Koch and S. Ullman, "Shifts in selective visual attention: towards the underlying neural circuitry." *Human Neurobiology*, vol. 4, no. 4, pp. 219–227, 1985.

[11] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. Wiley Interscience, 2000.

[12] T. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861–874, 2006.

[13] F. Bonnin-Pascual and A. Ortiz, "Combination of weak classifiers for metallic corrosion detection and guided crack location," in *IEEE International Conference on Emerging Technologies and Factory Automation*, 2010.

[14] ——, "Corrosion detection for automated visual inspection," in *Developments in Corrosion Protection*, D. M. Aliofkhazraei, Ed. InTech, 2014, ch. 25, pp. 619–632.