

Morphological operator-based approach for the detection and segmentation of defects on metal surfaces

Enfoque basado en operadores morfológicos para la detección y segmentación de defectos en superficies metálicas

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Summary. Currently, the detection of defects on metal surfaces is a highly relevant task in industrial processes with rigorous quality standards. In this sense, the timely and early detection of defects reduces machining and rework costs. To perform this task, current methods are expensive in terms of computational resources, limiting their applicability in real-world cases. This work proposes a lightweight approach for the detection and segmentation of surface defects in metal parts based on basic morphological operators. To achieve this, a strategy based on the use of weighted top-hat and bottom-hat morphological filters is combined to define areas with significant surface defects on a public dataset. The results, evaluated by visual inspection, show that the proposal based on mathematical morphology is a practical and efficient option for industrial inspection tasks.

Keywords: Mathematical Morphology, Defect Segmentation, Metal Surface Inspection, Image Processing, Industrial Image Analysis.

Resumen. Actualmente, la detección de defectos en superficies metálicas es una tarea de gran relevancia en procesos industriales con estrictos estándares de calidad. En este sentido, la detección oportuna y temprana de defectos reduce los costos de mecanizado y reprocesamiento. Para llevar a cabo esta tarea, los métodos actuales resultan costosos en términos de recursos computacionales, lo que limita su aplicabilidad en entornos reales. Este trabajo propone un enfoque ligero para la detección y segmentación de defectos superficiales en piezas metálicas, basado en operadores morfológicos básicos. Para ello, se emplea una estrategia que combina filtros morfológicos *top-hat* y *bottom-hat* ponderados con el fin de identificar áreas con defectos superficiales significativos en un conjunto de datos público. Los resultados, evaluados mediante inspección visual, demuestran que la propuesta basada en morfología matemática constituye una opción práctica y eficiente para tareas de inspección industrial.

Palabras Clave: Morfología matemática, segmentación de defectos, inspección de superficies metálicas, procesamiento de imágenes, análisis de imágenes industriales.

1 Introduction

Currently, defects caused by industrial machining processes and raw materials are unavoidable in the metalworking and manufacturing industries, where material quality plays a critical role in quality control. These defects can affect the functionality, safety, durability, and security of products machined from these raw materials. Therefore, inspection processes are usually performed by trained and specialized personnel; however, this process is slow and prone to human error, making it impossible to apply them to industrial processes with high-volume production lines.

In recent years, with the imminent arrival of Industry 4.0, process automation has created smart factories, improving the quality of the processes, products, and services they provide. This has contributed to the development of new automated methods based on image processing that allow visual identification of surface defects. However, current approaches and techniques tend to have a high complexity due to the implementation of deep learning, which requires large amounts of previous data and great computing power,

limiting the speed of large-scale image processing and its applicability in industrial scenarios [1]. In this sense, the theory studied by mathematical morphology (MM) through its basic morphological operators turns out to be a very useful tool, allowing noise reduction, segmentation and feature extraction in industrial process inspection applications [2].

This research paper proposes a morphological approach for the detection and segmentation of defects on metal surfaces, using reference images from a public dataset. The proposed strategy combines top-hat and bottom-hat morphological filters to highlight defects present on the surface. The image is subsequently thresholded and edge detection is performed. The results demonstrate the efficiency of the morphological operators and filters for early inspection, applicable to real-life industrial environments. Section 2 presents an analysis of current methods reported in the literature; Section 3 presents the overall methodology of the proposal, as well as details of the dataset used.

Section 4 analyzes the results, and Section 5 presents the conclusion and future work.

2 State of the art

For surface mechanical elements, a process prior to or after machining or after some thermal treatment that modifies the structure of the metal improving its characteristics is necessary, in order to observe defects on the surface, for this, techniques with destructive tests are chosen to see internal faults such as pores, corrosion or cracks. However, techniques based on non-destructive testing are usually a better option, for this there are techniques such as visual inspection, ultrasound, penetrating liquids, ferromagnetic particles, among others [3]. The application of computer vision inspection techniques is usually the best solution, these being classified into methods (i) by edge detection; (ii) threshold segmentation; and (iii) morphological transformations.

Within the first, we find the Sobel algorithm, which detects sudden changes in intensity in an image to define an edge; the Canny algorithm, which determines edges using the magnitude and direction of the gradient, after prior smoothing with a Gaussian filter to reduce noise; and the Laplacian filter, which highlights edges in an image based on a second-order derivative [4].

Threshold segmentation models implement global approaches such as the one proposed by Otsu, which aims to binarize the grayscale image's pixel values based on the histogram to determine the optimal threshold, maximizing the variance between classes [5]. In this sense, morphological filters are low computational complexity tools, making them ideal for filtering features in images, allowing noise removal, reinforcing edge detection, and improving the segmentation of areas or volumes of interest.

On the other hand, there are approaches based on Deep learning that are considered flexible, adaptable and more powerful compared to classical approaches. To mention supervised machine learning methods, we have the Support Vector Machine (SVM) that proposes a classifier that determines the best hyperplane/line that maximizes the distance between classes. Convolutional Neural Networks (CNN) are highly efficient, but have high computational costs and require a large amount of data, making them complex to design and interpret [6].

In short, traditional techniques remain reliable tools for performing automated visual inspections with good results, so it is necessary to develop combined strategies that improve results in industrial applications and quality control.

2.1 Mathematical Morphology in image processing

Morphological Mathematics (MM) according to J. Serra as the theory that analyzes spatial structures of the shape of objects. In a particular case of application is the processing of images focused on tasks of filtering and segmentation of images [7]. Morphological operators function as tools that allow by means of a structuring element to modify and analyze the shape and base structure of an image. These operators work by comparing a fixed structure called structuring element which is a subset of pixels of variable size and shape, where the variation of these characteristics changes the final result obtained, in the literature this structuring element of size $n \times m$ defined as λ , the most used are those of size 3×3 in the form of vertical, horizontal or complete lines. The morphological dilation operator described as $\delta \lambda (I)$ where the effect of

dilating the structure of an image based on its pixels has the effect of thickening the elements that meet the shape condition established by the structuring element λ , defined in Eq. 1.

$$\delta\lambda(I) = I \oplus \lambda = \{i|I \cap \lambda \neq \emptyset\} \quad (1)$$

The erosion transformation or operation consists of reducing the contour of objects just as water erodes stones, for all elements smaller than the structuring element. This operation, defined in Eq. 2.

$$\varepsilon\lambda(I) = I \ominus \lambda = \{i|\lambda i \subseteq I\} \quad (2)$$

Erosion is a image processing tool that allows noise removal in grayscale images, widely used in filters. These operations are applied to binary images, but at the same time they can be applied to grayscale images having other effects, lightening them for dilation and darkening them for erosion. On the other hand, the opening results from iteratively applying erosions and dilations in succession. The result of this process eliminates weakly connected objects, this process can be observed in Eq. 3.

$$\gamma\lambda(I) = I \circ \lambda = \delta\lambda(\varepsilon\lambda(I)) \quad (3)$$

Consequently, by inverting the order by first applying dilation and then erosion, morphological closure is degenerated. This process fills in structures that erosion cannot separate, improving and softening the contours of the bodies and filling in cracks or weak areas (see Eq. 4).

$$\varphi\lambda(I) = I \cdot \lambda = \varepsilon\lambda(\delta\lambda(I)) \quad (4)$$

On the other hand, the Top-hat filter results from subtracting the morphological opening from the original image, allowing bright elements smaller than the working structural element to be highlighted (see Eq. 5). On the other hand, the Bottom-hat transformation results from the difference between the original image and the morphological closure (see Eq. 6). The result is greater detail in dark areas such as cracks or surface stains.

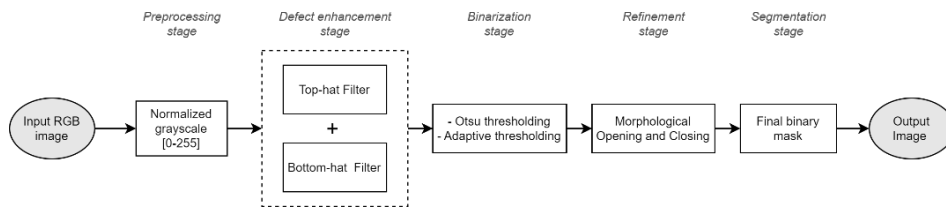
$$TopHat(I) = I - \gamma\lambda(I) \quad (5)$$

$$BottomHat(I) = \varphi\lambda(I) - I \quad (6)$$

3 Methodology used

This work proposes a simplified strategy that uses basic morphological operators and their conjunctions to detect and segment surface defects that are sometimes imperceptible to the naked eye, applied to a dataset of metallic surfaces. To this end, Fig. 2 shows the general process divided into 5 main stages. To better understand the process associated with each of these stages, they will be briefly described below.

Figure 2. Image processing stages for defect detection.



1. **Preprocessing stage.** The input image is converted to grayscale, where each pixel value takes a normalized value between 0-255, 0 indicates a dark gray and a high pixel value equals an intensity close to white.
2. **Defect enhancement stage.** The weighted combination of the images obtained by applying the Top-hat and Bottom-hat filters is sought, combining the benefits. Highlighting homogeneous defects that can be confused with the background. When seeking to highlight bright defects, a greater weight is assigned to I_{th} , and when seeking to highlight dark defects, greater weight is assigned to I_{bh} .

$$I_{enhanced} = \alpha \cdot I_{th} + \beta \cdot I_{bh} \quad (7)$$

3. **Binarization stage.** An appropriate threshold is calculated using the Otsu method to define the defects to be analyzed in the image, the first initial mask defined as I_{bin} .

4. **Refinement stage.** The initial mask I_{bin} contains pixels considered noise, represented as defects. To mitigate them, the Opening and Closing transformation is applied, improving the binary mask. To eliminate small regions that do not correspond to real defects, such as glare, it is improved with minimum area filtering, where the value of A_{min} depends on the size of the input image.
5. **Segmentation stage.** Finally, a final binary mask with minimal defects is compared to a reference mask I_{gt} to evaluate the quality and effectiveness of the strategy. At this point, the final mask represents a binary mask with a high level of noise cleanup and defined contours.

3.1 Algorithmic representation

The proposal was implemented in GNU Octave version 8.2.0, the freely distributed equivalent of Matlab. In order to use morphological tools such as erosion, dilation, opening, and locking, among others, it was necessary to install the image library with the following line of code: `pkg load image`. In the process of Algorithm 1 (see Figure 3), the input image of known dimensions is observed, after which the morphological filters are applied.

Algorithm 1 Morphological segmentation of surface defects

Input: Input image I_{in}
Output: Binary defect mask I_{mask}

$I_{in} \leftarrow \text{imread}()$ $I_{gray} \leftarrow \text{rgb2gray}(I_{in})$ $[0, 255]$	<i>Read image</i> <i>Convert to grayscale</i> <i>Normalize intensities in interval</i>
$I_{th} \leftarrow \text{imtophat}(I_{gray}, \lambda)$ $I_{bh} \leftarrow \text{imbothat}(I_{gray}, \lambda)$ $I_{enhanced} \leftarrow \alpha \cdot I_{th} + \beta \cdot I_{bh}$	<i>Apply Top-hat filter</i> <i>Apply Bottom-hat filter</i> <i>Combine images</i>
$T \leftarrow \text{graythresh}(I_{enhanced})$ $I_{bin} \leftarrow I_{enhanced} > T$	<i>Calculate Otsu threshold</i> <i>Binary image</i>
$I_{bin} \leftarrow \text{imopen}(I_{bin}, \lambda)$ $I_{bin} \leftarrow \text{imclose}(I_{bin}, \lambda)$ $I_{mask} \leftarrow \text{bwareaopen}(I_{bin}, a_{min})$	<i>Apply morphological opening operator</i> <i>Apply morphological closing operator</i> <i>Removing small objects</i>

return I_{mask}

Figure 3. Defect segmentation algorithm.

The output obtained is an image that represents the binary mask of surface defects in metal parts, segmenting them clearly and reliably. The results section is presented below, showing an excerpt from the experiment that illustrates the effectiveness of the proposal.

4 Experimental Results and Discussion

In order to validate the proposed strategy, the public dataset called Magnetic Tile Surface Defect Dataset [8] is used. This dataset is composed of six classes of defects (blowhole, crack, fray, break, uneven, free) on metallic surfaces, each with 1344 images of variable resolution, with a height range from 222 to 403px and from 103 to 632px wide, with a total weight of 48.44 MB.

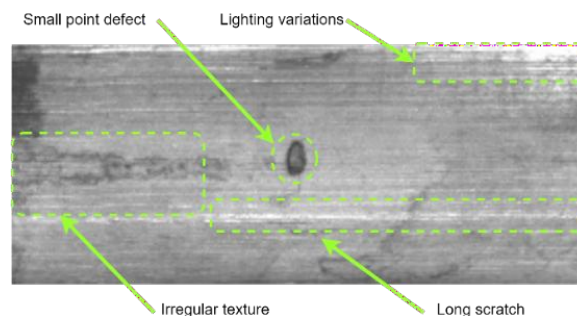


Figure 4. Cases of defects commonly found in metal parts.

Figure 4 shows the 4 cases of defects considered in this proposal, these being small point defects, long scratches, variations in the surface texture and variations in lighting.

4.1 Implementation details

The experimentation process includes native libraries that assist in image processing. Additionally, the *imread*, *rgb2gray*, *imdilate*, and *imerode* commands, among others, are part of the *image* library, which allows for efficient application of morphological transformations.

In an initial stage of preprocessing, the RGB color model of the images is converted to a grayscale simplification, which facilitates the implementation of intensity-based morphological operators on a single data matrix. The structuring element λ used for morphological filters and transformations is set to a test size of 3×3 , rather than 9×9 , depending on the image dimensions and the desired level of detail.

The average of the results obtained from applying the bottom-hat and top-hat filters is then obtained. This combination can also be performed using a weighted sum where the value associated with each filter will highlight one feature more than the other. This would require two additional parameters, α and β .

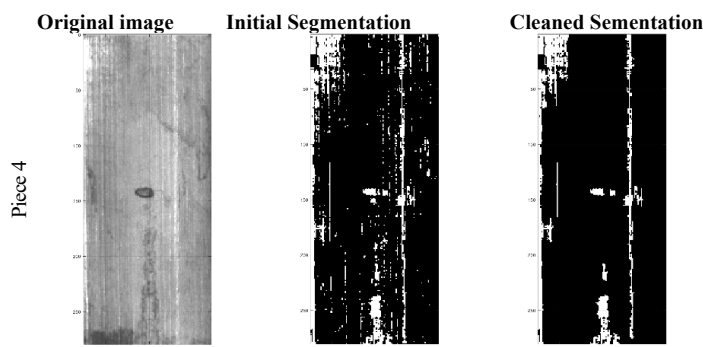
Finally, an adaptive threshold is implemented to construct the final binary mask where the detected defects can be observed. This threshold is calculated using the Otsu technique, making the process more robust to variations in ambient lighting.

On the other hand, the algorithm parameters were empirically adjusted until obtaining the best results in the analyzed images, where the structuring element was defined as a 10×10 square. The values that weight the sum of the application of the Top-hat and Bottom-hat filters are $\alpha = 0.7$ and $\beta = 0.3$ respectively. Finally, the image is filtered with areas of connected zones that do not comply with an $A_{min} \geq 25 \text{ px}$ value. In Fig. 5, the first column shows a sample of images of different sizes and conditions. The second column refers to the masks treated only with top-hat and bottom-hat filters and with dynamic thresholding. The last column refers to the final mask to which an area filter is applied, eliminating noise and poorly structured regions. This initial configuration varies slightly to obtain better results in images with different dimensions or evident variations in the lighting with which the dataset images were captured.

4.2 Discussion

The experimental process demonstrates that the correct combination of morphological filters, along with the appropriate definition of the algorithm's predominant variables, generates a robust and effective approach for detecting different types of defects found in images of metal parts used in industry. In addition to its computationally efficient nature, this strategy can be applied to systems with limited processing resources.

However, the proposal has limitations: when the image size changes and there are evident changes in lighting, the values of the variables of interest mentioned in subsection 3.2 must be adjusted to improve the results. Therefore, techniques that automatically adapt these variables are required to improve the results. The results demonstrate the effectiveness of morphological operators in segmenting areas of interest in industrial visual inspection applications.



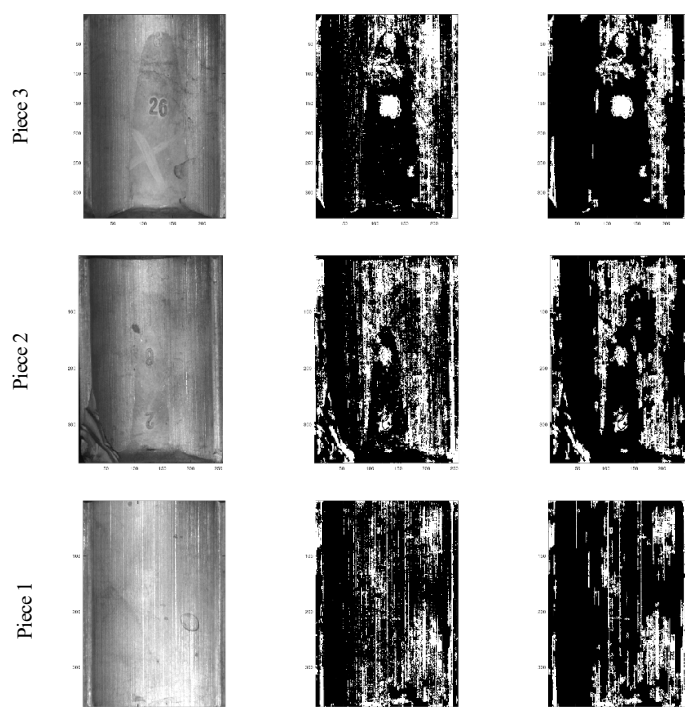


Figure 5. Result and comparison of the application of morphological filters in the final mask.

Table 1 provides a brief summary of the entire experiment. It shows the names of the images used, the number of pixels in the areas identified as defects in the initial, unfiltered mask, and, in the third column, the number of pixels in the final mask after morphological filtering. Finally, the last column shows the percentage reduction in pixels that could be considered noise.

Table 1. Number of pixels detected as defects in the initial mask and after final filtering.

Image	Initial mask size (px)	Final filtered mask (px)	Noise reduction (%)
exp6_num_114490	20,862	17,137	17.86
exp2_num_4964	5,224	3,714	28.91
exp2_num_20390	14,740	12,903	12.46
exp2_num_54273	8,717	6,174	29.17
exp2_num_291023	15,526	12,665	18.43
exp3_num_4764	2,378	1,835	22.83
exp3_num_36246	8,257	6,706	18.78

5 Conclusions and Future Work

The strategy proposed in this work demonstrates the feasibility and application of morphological operators in image processing as an effective approach for detecting defects on metallic surfaces. The combination of top-hat and bottom-hat filters, summed in a weighted manner, can eliminate specific irregularities and reduce the noise present. The results show a reduction in detected noise levels ranging from 12.46% to 29.17%. This demonstrates its application in industrial contexts, proving to be a viable and robust option for automatic analysis.

The methodology can be applied and generate an automatic adaptation system for the variables of interest as future work. Furthermore, it can be complemented by operators and techniques that help classify and dimension the defects found, expanding its application to a large number of materials.

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