

Computer Vision Techniques Applied to the Quality Control of Ceramic Plates

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Abstract – This paper presents a system, based on computer vision techniques, that detects and quantifies different types of defects in ceramic plates. It was developed in collaboration with the industrial ceramic sector and consequently it was focused on the defects that are considered more quality depreciating by the Portuguese industry. They are of three main types: cracks; granules and relief surface. For each type the development was specific as far as image processing techniques and illumination are concerned. The system was tested in pre industrial conditions showing the efficiency of the several developed algorithms and also revealing the perspective of its evolution to an industrial automatic inspection system.

I. INTRODUCTION

In the last years the ceramic industry has been subject to relevant developments related with the progression of automation. The plate manufacturing sector is one of the most innovative regarding the application of new technologies in the several production stages. However quality control remains as an exception since the detection of defects stills as a manual operation. Consequently the human influence is significant and results in a low quality inspection due to human subjectivity and fatigue. An automatic system can provide many economical and safety benefits such as: to reduce human presence in a difficult environments and human error; to increase efficiency and stability in the process; to promote faster and more economic inspection.

Computer vision techniques can make available an effective solution to this automatic quality control. This article presents such a computer vision system able to inspect ceramic plates. The plates have round shape with a maximum diameter of 17in, without patterns and uniform in what color concerns.

The more relevant defects are classified in three categories: cracks; granules and relief surface. The cracks are rips throughout the plate surface that can be noticed as relief variations. They present variable length (few mm to some cm) and a width below 0,5mm. Granules result from the inclusion of impurities during production process. They have normally a circular shape and a variable dimension with at least 0.1mm of diameter. The relief surface presents a cluster of small bumps in a particular area of the plate. The bump is a round and raise area on the surface. The relief surface can have different forms and sizes according to the bumps agglomeration. Fig. 1 presents an example of each defect.

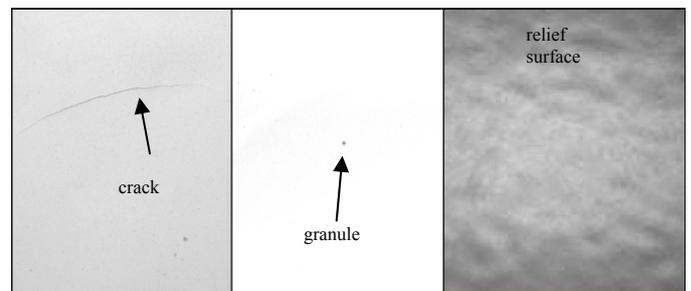


Fig. 1. Example of the three classes of plate defects: crack, granule and relief surface.

According to the performed bibliographic research there aren't available computer vision solutions for plate inspection. In fact, the visual inspection by image processing and analysis is still an emerging technology in the global ceramic industry. The tiles production sector has been one of the most prominent sector concerning the research and development of vision techniques and prototypes [1-6]. Those techniques, based on adaptive segmentation and edge detection, were also used for the

development of the present work dedicated to plate inspection.

II. METHODS

The detection of the defects comprises two phases: segmentation and identification (Fig. 2). The main purpose of the segmentation is to isolate the defect from the plate background. Then, the identification modules extract relevant blob features from the segmented image in order to classify the defect. For each type of defect a specific set of algorithms was developed and implemented.

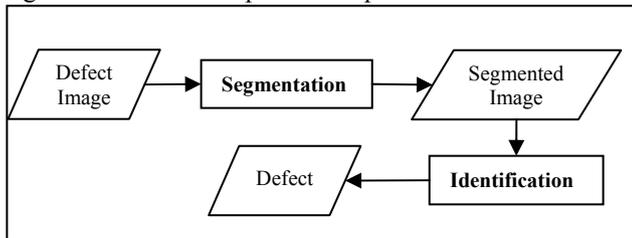


Fig. 2. Block diagram of the detection procedure.

A. Algorithms for crack defect detection

The segmentation for cracks is based on the Canny Edge detector algorithm [3,7,8] (Fig. 3). This algorithm imposes a first step (smoothing) for noise reduction through the application of a Gaussian filter. The next step (enhancement) starts by calculating the magnitude and direction of the image gradient.

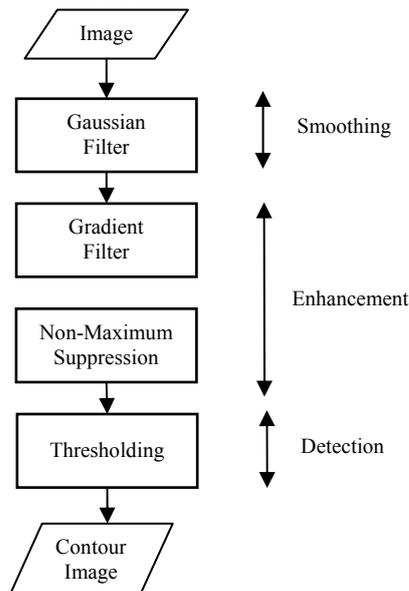


Fig. 3. Block diagram of the Canny edge detector.

After the directions are known, a non-maximum suppression verifies each point in the gradient direction to eliminate all the points that are not a maximum gradient. This operation results in an edge described by a thin line in the gradient image. Finally, the detection stage applies a threshold procedure controlled by two values (T1 and T2), to the maximum points, in order to reduce the number of

false edge segments. Any pixel in the gradient image that has values greater than T1 is considered as a possible edge pixel. If any of these possible edge pixel has a value greater than T2, it is selected as an effective edge pixel. The described sequence of operations results in a contour image, concluding the segmentation phase (Fig. 4).

The identification phase (Fig. 4) begins by dilating the segmented image. This procedure is applied to minimize the possibility of broken edges segments, which is a common problem arising from the thresholding. The Find Contour process, based on the chain code [9], returns a sequence with all the contours of the segmented image. Then, the Get Cracks algorithm distinguishes the cracks from other extracted contours (e.g. noise, granule).

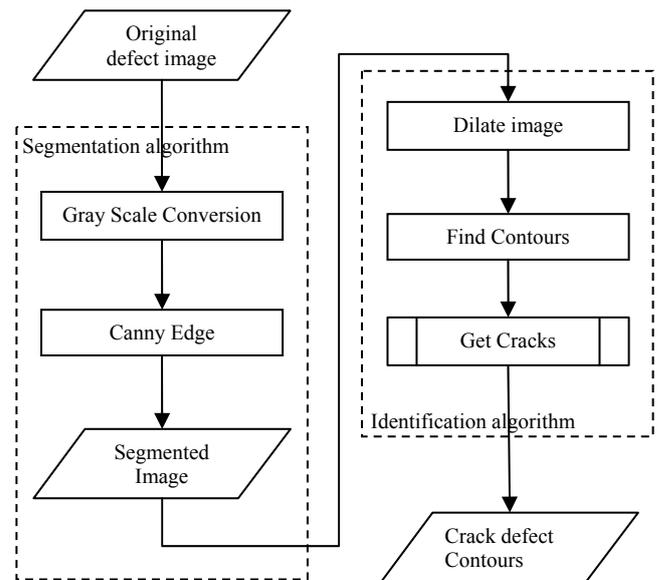


Fig. 4. Block diagram of crack defect detection algorithms: Segmentation algorithm; Identification algorithm.

Fig. 5 details the Get Cracks process. For each contour of the sequence, a 2D box is created in order to engage the minimal rectangle area of the contour, as shown in Fig. 6.

The box width and height permit the calculus of a ratio, which is the feature used to classify the crack defect. A common crack presents an elongated shape, resulting in a ratio typically higher than a pre established threshold (RT). When the system identifies a defect that is not a crack, that contour is eliminated from the sequence. At the end, the algorithm returns only the cracks contours.

B. Algorithms for granule defect detection

Fig. 7 describes the Granule defect detection algorithms. The segmentation uses an adaptive thresholding algorithm [9,10]. This is a convenient approach taken in account the small size of these defects and the illumination conditions that are difficult to make completely uniform. In this method, the image is subdivided in regions, in such a way that the illumination is more uniform in each region. This

can be obtained by calculating a threshold for each pixel. The threshold was determined by examining the neighborhood and extracting a statistical value, specifically the mean value of the intensity dispersion. The size of the neighborhood is a compromise as it has to be large enough to get a significant statistical value and small enough to maintain the uniformity of the illumination. The result is a binary image, further submitted to an open morphological operator. That eliminates the noise remnant from the binarization, concluding the segmentation process.

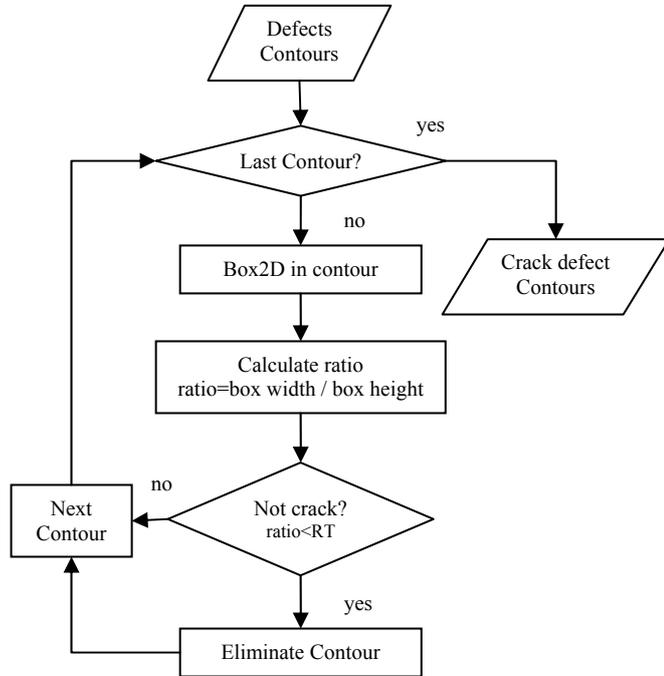


Fig. 5. Block diagram of the Get Cracks algorithm.

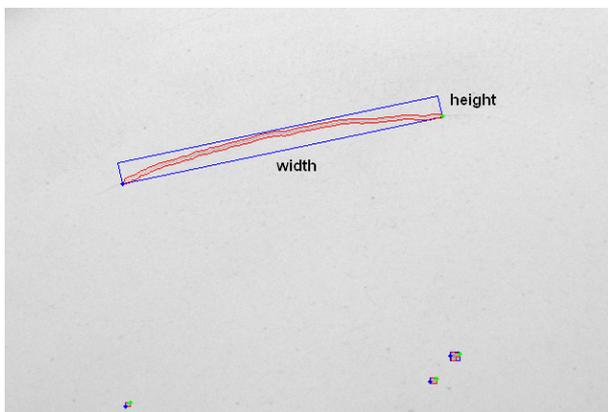


Fig. 6. Image of the Contours and a 2D Box of the defects.

The identification phase begins applying the segmented image to the identification algorithm developed for cracks (described previously). After extracting the contours of the potential cracks, they are drawn in a filled way, which results in a new image with black background and white filled contours. After a dilatation operator, the segmented image holding only granules is obtained by applying an OR

logical operation between the segmented image (with all defects) and the potential crack image. In this way it is possible to exclude the crack areas of the original image. Finally the contours of the granules are obtained through the Find Contours process.

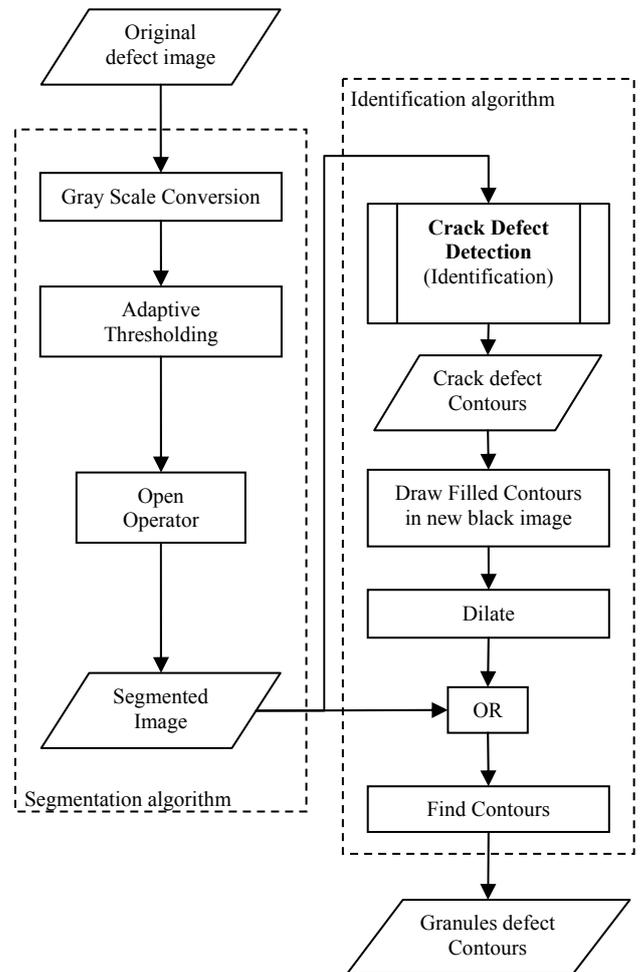


Fig. 7. Block diagram of granule defect detection algorithms: Segmentation algorithm; Identification algorithm.

C. Algorithms for relief surface detection

The detection of these defects is based on the principle of specular reflection [11]. When a very smooth surface is illuminated, it is possible to acquire a bright area, with the same color of the illuminator that is caused by specular reflection. This is dependent of the point of visualization. Fig. 8 illustrates this principle when it is applied to a plate with and without relief surface defects.

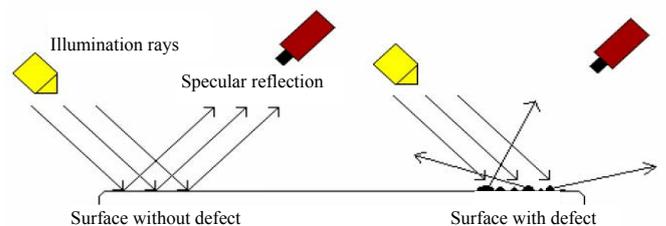


Fig. 8. Specular reflection at plate surfaces.

Fig. 9 shows real illuminated images of plate surfaces, with and without relief, obtained using specular reflection. Since in the image with defect the surface is not smooth, the reflection will have a higher dispersion than in the image without defect. Therefore to make a distinction between these two situations it was necessary to define a region of process - region of interest (ROI), as shown in Fig. 9 between the two lines. The level of dispersion in this area gives indication about the presence and respective degree of relief.

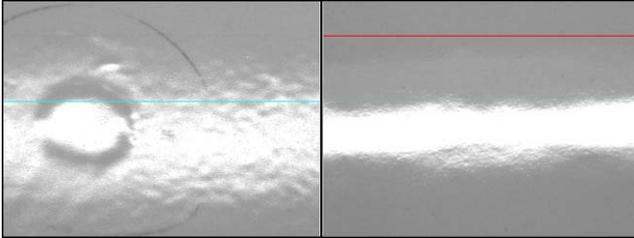


Fig. 9. Image with (left) and without (right) relief surface defect, affected by specular reflection.

The detection algorithm comprises an approach that extracts statistical values from the binarized ROI image and an approach that extracts statistics from the gray level ROI image (Fig. 10).

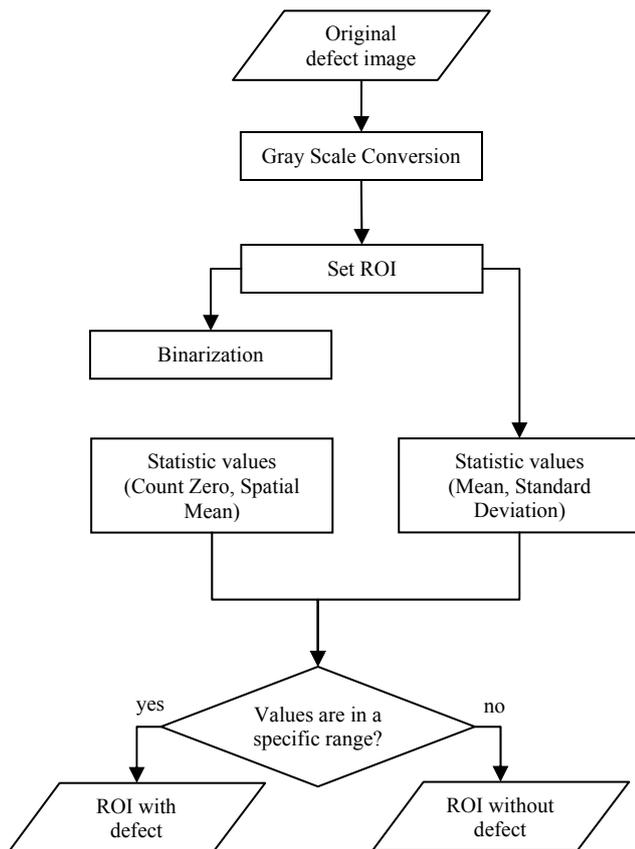


Fig. 10. Block diagram of relief surface detection Algorithm.

In the first approach, the binarization is accomplished by defining a static threshold value. From the segmented image it is possible to obtain statistical information used to quantify the relief dispersion, such as the number of pixels in the ROI that have zero value and a spatial mean of all these pixels.

In the second approach (without binarization), the mean and standard deviation of the intensity of the ROI pixels are calculated.

Statistics obtained by the two approaches must then be evaluated concerning their inclusion within a specific range. A plate will be considered without relief defect if all the values are outside the defined range.

III. RESULTS AND DISCUSSION

The system comprises two different setups: one for the detection of cracks and granules and another for the relief surface evaluation. In both cases the plates are moving in a belt convey passing under the illumination system.

In the first case it is important to minimize problems, such as flicker and specular reflections. For that a specific illumination setup was projected. The illumination is based on LEDS light, in a frontal position. This must simulate a kind of cloudy day light, which was achieved with a white calotte (Fig. 11) in a diffuse material where fluorescent light points towards the calotte interior. The result is an image with a high degree of illumination uniformity on the plate. A global plate image is acquired by an Allied VC OSCAR F810C progressive camera (res: 3288x2470 pixels) with a 16mm lenses and a firewire acquisition board.

In the case of relief surface detection for each acquisition only a ROI of the image plate is inspected. To cover the entire plate several acquisitions must be performed, as in a linear acquisition process. The setup is based on a bar of LEDS and in an Allied VC MERLIN F-033C progressive camera (res: 656x494 pixels) with a 16mm lenses and a firewire acquisition board. The light source and the camera were positioned as illustrated in fig. 8. This configuration creates the desired specular reflection on the plate image.

The application was developed with Microsoft Visual C++ and with the OpenCv Library [12] that includes several image processing and computer vision algorithms. Two modules were included: one to parameterize the system establishing the parameters for the image processing algorithms and a module to carry out the detection of the defects.

Several supervised tests were performed with the described setups and using a set of known samples (500) representing the diversity of situations concerning types, dimensions and spatial distribution of defects. This allowed determining the parameters, for each algorithm, that best discriminate the three types of defects (Table I and II).

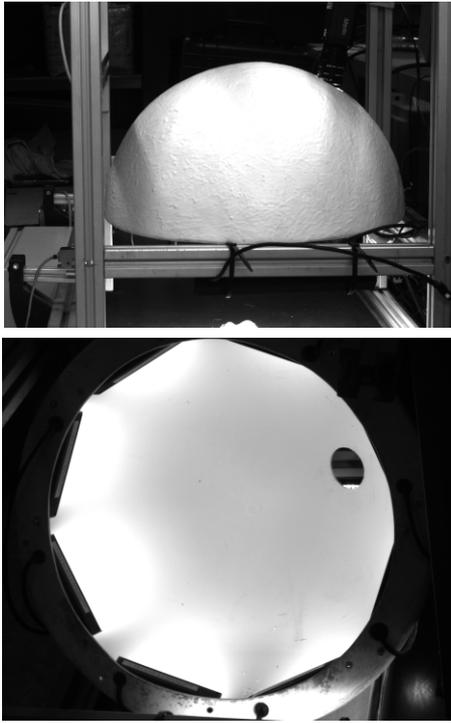


Fig. 11. Images of the calotte used on the setup for the detection of cracks and granules.

TABLE I
SYSTEM PARAMETERS FOR CRACK AND GRANULE DETECTION.

	Canny Operator		Ratio Threshold (RT)	Neighborhood Size
	T1	T2		
Crack	42	126	2	-
Granule	-	-	2	35

TABLE II
SYSTEM PARAMETERS FOR RELIEF SURFACE DETECTION.

ROI	Lower Limit	Upper Limit	
	141	197	
<i>Binarization Approach</i>			
	Threshold	Spatial Mean	Count Zero
Range (Fig. 10)	180	<140	>30000
<i>Without Binarization Approach</i>			
	Mean	Standard deviation	
Range (Fig. 10)	>160	>10	

Figs. 12 and 13 exemplifies the application of the system to detect cracks and granules, respectively. In both, the final result is a sequence of image points that defines the contours of the defects.

Fig. 14 illustrates an application example for relief surface detection in accordance with the algorithm of fig. 10. This figure shows the original images for a defective (Fig. 14a) and a non defective (Fig. 14b) plate and the respective segmented images using the binarization process. Table III presents the statistic values that describe the ROI marked in the original images. Comparing these statistics

with the values specified in table II it is possible to demonstrate the presence of the defective plate.

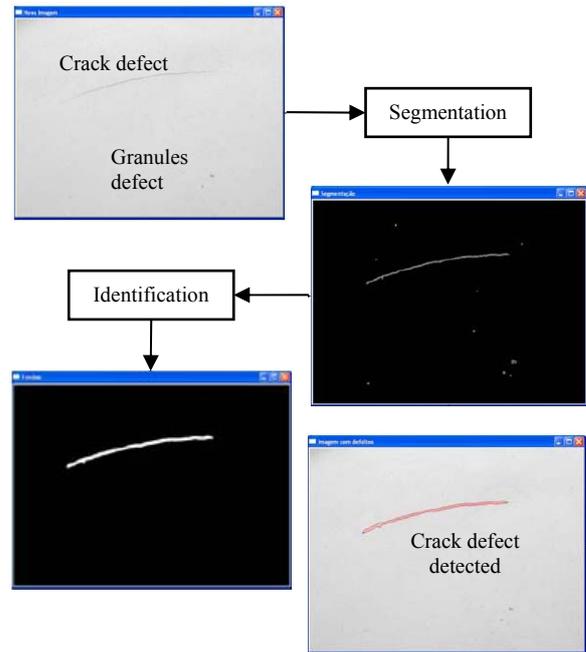


Fig. 12. Sequence of images for the crack defect; from top: original, segmented and the defect contour drawn in the original image.

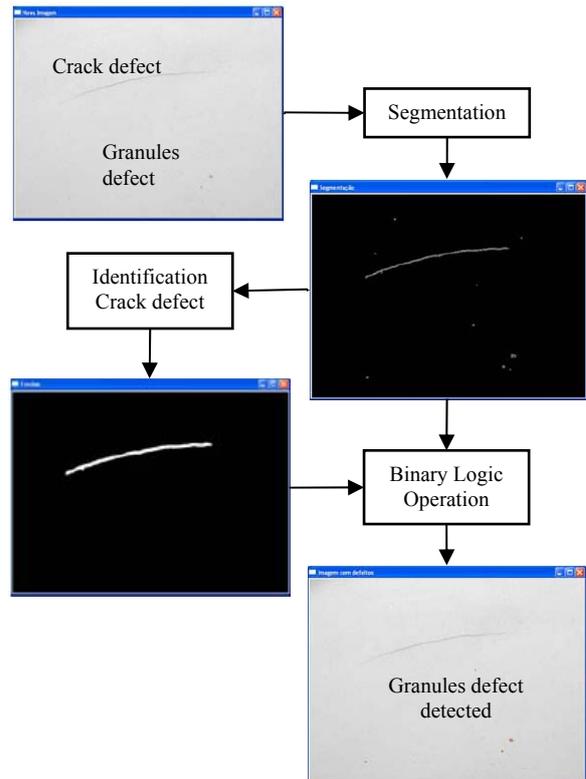


Fig. 13. Sequence of images for the granule defect; from top: original, segmented and the defect contour drawn in the original image.

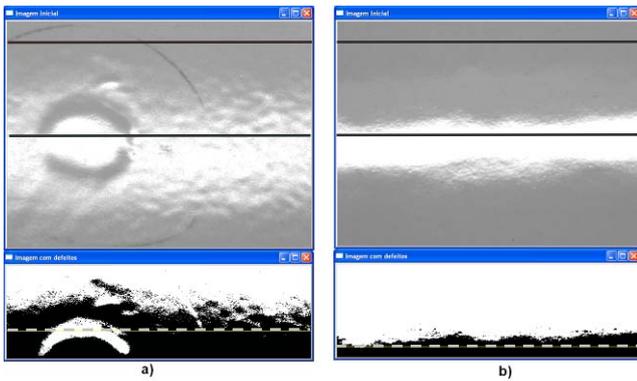


Fig. 14. Original and segmented plate images. a) Defective surface; b) Non defective surface. Solid line defines the ROI. Dashed line represents the spatial mean.

TABLE III
APPLICATION RESULTS FOR THE EXAMPLES FROM FIG. 14.

	Defective	Non Defective
Mean	175	157
Standard Deviation	19	8
Count Zero	62276	25190
Spatial Mean	136	172

IV. CONCLUSIONS

This paper describes a computer vision system dedicated to identify the more relevant defects that were found to depreciate the ceramic plates from Portuguese industry: cracks, granules and the presence of relief surfaces.

For the different types of defects, specific image processing and analysis algorithms were implemented as well as laboratory setups representing industrial conditions, namely concerning illumination. For each defect a set of parameters were identified to allow a higher flexibility of the system.

The tests performed with the lab prototype suggest good performance. Therefore, this work demonstrated the viability for implementing an automatic quality control solution based on visual inspection, which will fulfill a technological demand that persists in this industrial sector.

REFERENCES

- [1] C. Boukouvalas, J. Kittler, R. Marik, M. Mirmehdi and M. Petrou, "Ceramic Tile Inspection for colour and structural defects". in Proceedings of AMPT95 pages 390--399. August 1995.
- [2] Suzana Vasilic, Zeljko Hocenski, "The Edge Detecting Methods in Ceramic Tiles Defects Detection". in IEEE International Symposium on Industrial Electronics, 2006, July 2006.
- [3] Zeljko Hocenski, Suzana Vasilic, Verica Hocenski, "Improved Canny Edge Detector in Ceramic Tiles Defect Detection". in IEEE Industrial Electronics, IECON 2006 – 32nd Annual Conference, Novembro 2006.
- [4] Desoli, G.S.; Fioravanti, S.; Fioravanti, R.; Corso, D. "A system for automated visual inspection of ceramic tiles". in International Conference on Industrial Electronics Control and Instrumentation, 1993.

- [5] Elbehiery, Hussam M., Hefnawy, Alaa A., Elewa, Muhammad T., "Visual Inspection for Fired Ceramic Tile's Surface Defects Using Wavelet Analysis". in GVIP(05), No. V2, January 2005.
- [6] Peter Nold, Ralf Löbe, and Klaus Jean Frey, "Ceramic Industry – state-of-the-Art Processing", Maschinenfabrik Gustav Eirich, Hardheim, Germany, unpublished.
- [7] William K. Pratt, "Digital Imaging Processing", fourth edition, Wiley, 2007.
- [8] Bill Green, "Canny Edge Detection Tutorial", web page visited on September 2007, www.pages.drexel.edu/~weg22/can_tut.html
- [9] Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing", Second Edition, Prentice Hall, 2002.
- [10] Bob Fisher, Simon Perkins Ashley Walker, Erik Wolfart, "Hyper Media Image Processing Reference – Adaptive Thresholding", web page visited on October 2007. www.cce.hw.ac.uk/hipr/html/adpthrsh.html
- [11] Tinku Acharya, Ajoy K. Ray, "Image Processing – Principles and Applications", Willey, 2005
- [12] Intel, "Open Source Computer Vision Library" web page visited on September 2007. www.intel.com/technology/computing/opencv