Quality Control in Porcelain Industry based on Computer Vision Techniques

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***Abstract*—This paper presents a system based on computer vision techniques for quality monitoring the porcelain production flow. The quality monitored system is based on the robot-computer vision architecture and includes: (i) real-time high-speed processing of product images, and (ii) a global autonomous behaviour, context and task dependent self-learning that is adaptive to the work environment. We have investigated the use of integral Robot Vision (iRVision) technology. iRVision is a ready-to-use robotic vision package available for FANUC robots. The experimental evaluation shows that the inspection system that we developed can correctly identify if a product is defective or not. The proposed architecture will finally have a positive economic impact for the company by optimizing the production flow and reducing the production costs.**

I. Introduction

This paper presents a project aiming to monitoring the manufacturing process of porcelain. The project is a collaboration with an economic agent. The economic agent is a company with Romanian capital, European leader in the porcelain industry which has over 200 industrial robots used in the manufacturing process of porcelain.

The manufacturing process of the porcelain consists of the following steps: 1) Preparation of the ceramic mass. 2) Powder atomisation. 3) Forming and pressing the object. 4) Burning I. 5) Glazing. 6) The combustion II. 7) Final sorting. Quality control and removal of defective products is done after Burning 1 (phase 4), Glazing (phase 5) and Final Sorting (phase 7). The quality requirements of the customers have become very high, thus the company is obliged to deliver only first quality products. Simultaneously, the product inspection criteria have become very diverse, the number of products inspected has increased and also the complexity of control tasks. Defects are due to some factors and parameters of the technological process. Defects can be classified into several categories such as: asymmetries, curves, deformed edges, degraded color, glaze leak traces of retouching, flaking, fissures, cracks, indenture, scratches, etc.

Currently, the company does not have an automatic system for the identification and classification of defects, this activity being executed by employees. The checking of products and identifying defects is performed visually and by touch by the employees. For economic reasons, it is necessary that quality control requirements should have limited effect on the costs and production times, which led to the need of finding solutions for automated inspection.

Our project investigates how to develop an intelligent system based on machine learning and computer vision which will monitor and innovate the current production flow. The specific objectives of the project are: reducing the manufacturing time at each processing phase, optimizing the production efficiency by eliminating defective products, improving the monitoring and control system of the entire flow by adding new functionalities to the current computer vision system, and increasing the innovation capacity of the economic agent. A significant result will be the monitoring and quality control system implemented in real time and its integration into the company decision-making system. Defects will be identified and classified at every operational phase. The quality monitored system is based on the robot-computer vision architecture and includes: (i) real-time high-speed processing of product images, and (ii) a global autonomous behaviour, context and task dependent self-learning that is adaptive to the work environment.

The paper is structured as follows. Section II presents related works. Section III describes system design and implementation. Section IV presents the details of the experimental evaluation. Section V concludes.

II. Related Work

Visual inspection by image processing is an emerging technology in the ceramic industry [1], [2], [3], [4], [5]. An exception is the tiles production sector, in which research and development of vision techniques and prototypes have been reported [6], [7], [8], [9], [10], [11], [12]. The techniques used are based on adaptive segmentation and edge detection and are dedicated to identify the more relevant defects that were found to depreciate the ceramic plates. In [13] it is proposed a technique for detecting surface defects such as cracks, spots, pinholes, and blobs using shape feature extraction through morphological operations. Several approaches investigate systems for defect detection based on acoustic emission sensors, computer vision techniques and a large memory storage and retrieval artificial neural network.

Only a few works investigate the automated quality control in the porcelain ware manufacturing sector [14], [15]. The Standardization on the determination of ceramics quality has been established by the International Standard Organization (ISO) in the SNI ISO 10545-2:2010 document [16].

Defect detection in ceramic products has been investigated with deep learning techniques in [17] and it was shown that deep learning performed better in comparison to other learning algorithms. Furthermore, defect detection in porcelain ware data was investigated using Active Learning and Transfer Learning techniques [18].

III. System Design and Implementation

A. Robot Manipulation

The quality monitored system is integrated in the production flow porcelain as follows:

1) The product reaches the inspection system.
2) The sensor detects the product and sends a signal of artificial vision system.
3) Illumination of the product.
4) The artificial vision system receives the image from the sensor.
5) Software algorithms running on the artificial vision system process and analyze the received image.
6) The vision system sends visual signals to an industrial robot that acts as a diverter if the product is defective.
7) The human operator visualizes the rejected products, statistics in progress, and can turn off the system if necessary.

Figure 1 shows a lab prototype that performs the steps described above.

B. iRVision

iRVision (integral Robot Vision) [19] is a ready-to-use robotic vision package available on FANUC robots. This vision system allows easy manipulation of FANUC robots for positioning or fault detection. The acquisition and processing of the image is done by the robot controller. iRVision system has the following components: camera and lens (or three-dimensional laser sensor), camera cable, lighting equipment and camera multiplexer. iRVision measures the position of each item, in our case ceramic plates, by using cameras, and it adjusts the robot motion so that the robot can manipulate the plate.

iRVision includes a function named iRVision Inspection that is the main function used in our investigation. This function is used for evaluate if a target image passes or fails, based on specified conditions. First, the function snaps the image, preprocesses the image and evaluates it. The iRVision Inspection automates the visual survey that has been performed manually before.

The iRVision function has many features that can be performed on the target and further on extracted: brightness, position, length, number of parts, area of an image. It evaluates if each features respect all the conditions and determines if the target passes or fails inspection. The result of inspection (pass or fail) logically combine the evaluation results. For inspection performing vision processes are used with several vision tools. We used ”Single-View Inspection VisProc” as vision process. An Inspection vision process usually has an evaluation tool and some command tools. Command tools are added according to the details of inspection. Command tools are divided into four types: locator tool, measurement tool, evaluation tool and others.

A locator tool makes different operations like image processing for a snapped image, detects a target in an image and outputs the position where the target is detected. It outputs the score, contrast and others characteristics of the detected target as measurement values. Most of the locator tools can be used for: location, counting number of parts, checking presence/absence, measuring length, measuring area.

1) GPM locator tool: GPM locator tool is used for detecting a geometry taught as a model pattern in an image and outputs the position of the geometry detected in the image. The contour line is used for detecting the position of the target accurately. GPM locator tool outputs the following measurement values for inspection: position, angle, size, aspect ratio, skew angle, score, fit error and contrast.

Measurement tools perform image processing, detect a target in an image, outputs the position where the target is detected. It outputs the score, contrast and other characteristics of the detected target as measurement values. The measurement tools are:

2) Histogram tool: This tool measures the brightness of an image. It can be used in applications like type identification and in evaluation of impurity. Histogram tool has several measurement values for inspection: number of pixels, brightness of brightest pixel, brightness of darkest pixel, median of brightness, mode of brightness, standard deviation of brightness, ratio of pixels within the range and ratio of pixels outside the range.

3) Surface flaw inspection tool: Surface flaw inspection tool is used for finding defects on the surface of a target object. This tool can be used for counting number of defects, finding defects on molded plastics or on the metal surfaces. It has the following measurement values for inspection: number of defects, total area, flaw ratio, inspected ratio, max area, max perimeter, max magnitude.

Evaluation tool evaluates if a target passes or fails inspection. It receives measurement values output from other tools, like locator and measurement, and outputs the evaluation result by checking the specified conditional expressions. Several conditional expressions can be defined. All inspection vision processes need to have at least one evaluation tool. The Single View Inspection has only one evaluation tool.

IV. Experimental Evaluation

In this section we describe the data set (Section IV-A) and how to detect three types of porcelain defects: cracks and deformations using GPM locator tool (Section IV-B), surface defects using Surface flaw inspection tool (Section IV-C) and bumps and texture defects using Blob locator tool (Section IV-D). In (Section IV-E) we describe a combined inspection for cracks and surface defects.

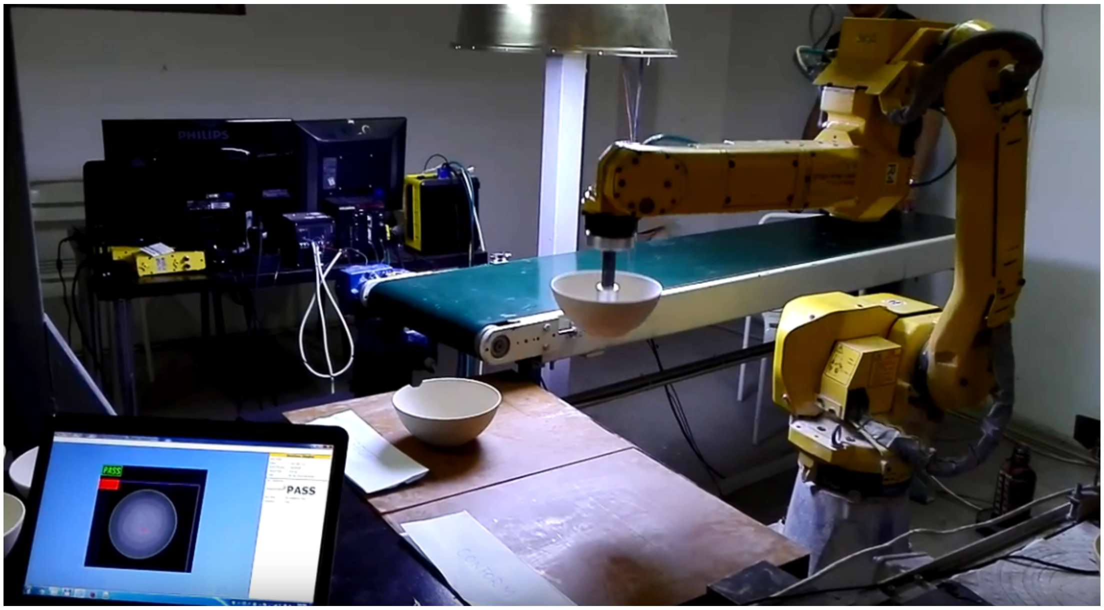

Fig. 1. A lab prototype showing how the quality control system will be integrated in the production flow porcelain flow. The following steps are performed: 1) The product reaches the inspection system. 2) The sensor detects the product and sends a signal to the artificial vision system. 3) The product is being illuminated and the image is acquired. 4) The artificial vision system receives the image. 5) Software algorithms running on the artificial vision system process and analyze the received image. 6) The vision system sends a signal to an industrial robot that acts as a diverter if the product is defective. 7) The human operator visualizes the rejected products, statistics in progress, and can turn off the system if necessary.

A. Data set

For experimental evaluation we used a data set containing different types of porcelain ware images. The images were collected from our industrial partner. Figure 2 shows samples of different types of defects in the porcelain image data set that we used for experimental evaluation.

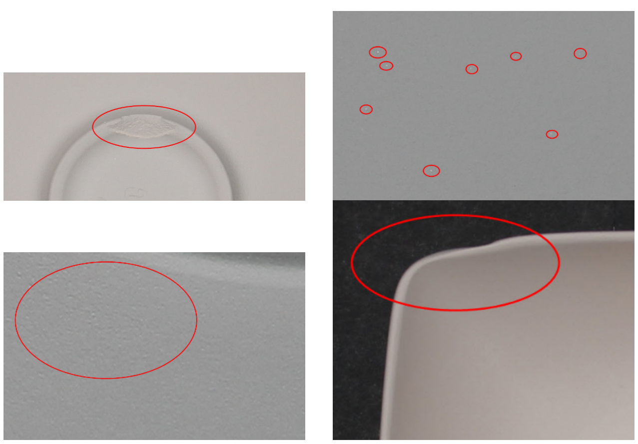

Fig. 2. Different types of defects in porcelain image data set. From left to right: deterioration after pressing, bumps, texture defects, margin deformation.

B. Cracks and Deformations

In the porcelain industry, most of the defects are cracks and deformations. We investigated how to identify these types of defects using GPM locator tool.

GPM locator has the following parameters: training mask, emphasis area, score threshold, contrast threshold, area overlap, elasticity, ignore polarity, orientation, scale, aspect, etc.

- Training mask is used when the pattern model has any unnecessary items in the background. We used most of parameters as default, less elasticity and ignore polarity.
- Elasticity is a parameter which specify a pixel value to indicate how much the pattern in the image is allowed to be deviated in geometry from the taught model. We set elasticity to value of 0.6 pixels because we want to detect cracks or deformation of the plate. The default value of elasticity is 1.5 pixels.
- Ignore polarity parameter was checked for our inspection because we wanted to ignore dark/light zones of the trained model pattern.
- We unchecked orientation and scale boxes, but we checked the aspect. We unchecked the orientation box because in this case our plates are rounds and this parameter searched for a rotated model.
- We checked aspect box because if it was unchecked the aspect ratio was ignored.

GPM locator outputs several parameters. We have chosen the score of the found pattern as variable for evaluation. For our data set, if the score is bigger than 99.3 then the target passes the inspection, else the target fails the inspection.

Figure 3 shows the plate quality evaluation for cracks and deformations. The top image shows a correct plate which pass the inspection. The middle image shows a plate with one crack. The crack was automatic highlighted by GPM locator tool with a red line. The bottom image from Figure 3 presents a failed inspection because GPM locator detected a deformation defect. The deformation was marked with a red line.

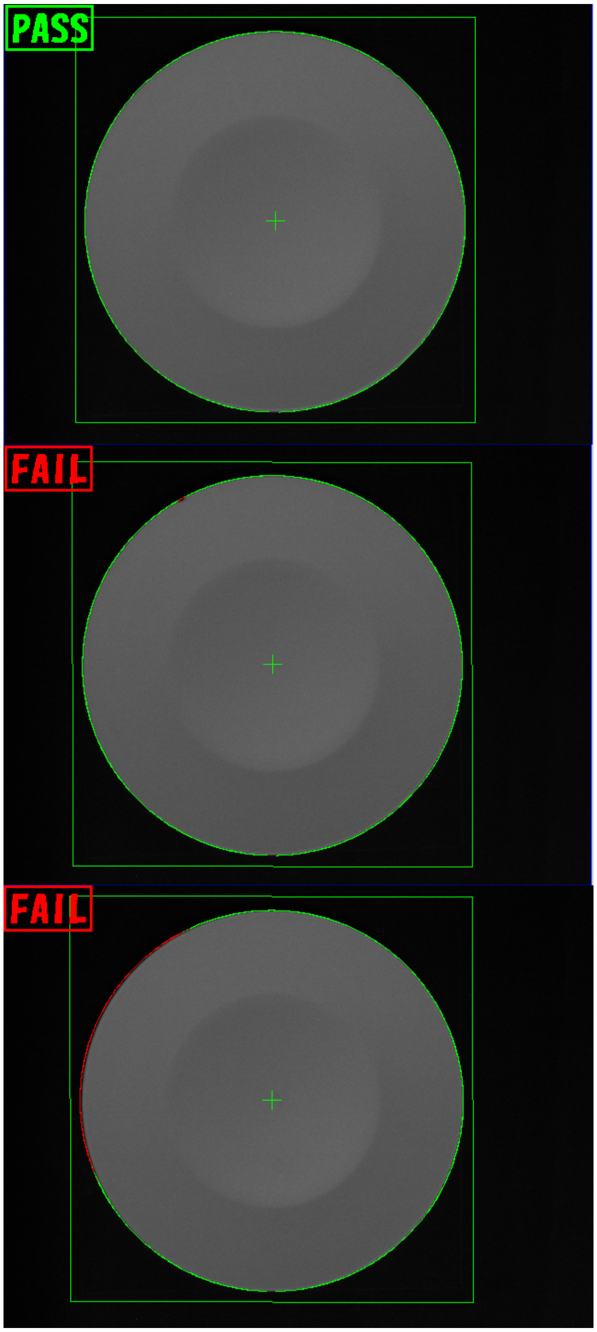

Fig. 3. Evaluating flaws like cracks and deformations on plates. First image: Passed inspection. Second image: Failed inspection because of cracks in the plate. Third image: Failed inspection because of deformation of the plate.

C. Surface Defects

We used Surface flaw inspection tool for defect detection on the surface of the plate. First, we selected the image which was used for training area for inspection. The image which is used for training must have a correct surface and will be used as a pattern. Surface flaw inspection tool has several parameters: run-time mask, flaw color, contrast threshold, magnitude range, area, perimeter, etc.

- Run-time mask specifies an area of the search window that is not of interest for inspection. We set this parameter as disable because we do not have an image with noise, the background of image being black.
- Flaw color shows the color of the flaw in the surface. For flaw color parameter we used black value because the cracks are black in the plate surface.
- Contrast threshold specify how clearly the contour is perceivable in order to be considered as a flaw. We set the value for contrast threshold to 1 because in the plate surface are faint flaws. The default value for this parameter is 10.
- We used magnitude range parameter as default value (10 for minimum and 200 for maximum). This parameter specifies the magnitude which is determined as the difference between the darkest gray within the found flaw region and the gray of the contour.

For evaluating if the target passes or fails the inspection we created a variable which counts the number of defects. For passing the inspection, this variable must be equal with 0. If the variable is different of 0, the inspection fails.

Figure 4 shows examples of images that passed (top image) and failed the surface inspection (bottom image). The system correctly identifies that the bottom image is defective and the flaw, which is represented by some crack on the surface of the plate is highlighted in red.

D. Bumps/Texture Defects

Some plates have bumps on their surface. We used Blob locator tool for bumps detection. For making the pattern we selected an image without bumps. Using Blob locator tool we binarized it (black-and-white image) and the surface of the plate was all white. We used threshold parameter for binarized image. Threshold makes a distinction between the object and the background. When the tool makes the inspection, it compares the new object with the pattern model. If the inspected object has some blobs in addition to the pattern then the object has bumps. If a plate has bumps then a circle will be drawn around them.

For evaluation we used score as variable. If the score is bigger than 99.5 the target passes the inspection, else it fails the inspection.

Figure 5 shows a passed and a failed inspection for texture defects evaluation. The top image shows a passed inspection because the plate from the image is similar with the pattern, it has no bumps. In the bottom image of the figure the target fails the inspection because the plate has bumps and it has blobs in addition to the pattern model.

E. Combined inspection

It was created an inspection model for cracks and surface defects detection on a plate. For the inspection we used GPM Locator tool, Histogram tool and Surface flaw inspection tool. The GPM Locator was used to detect the plate regardless of its

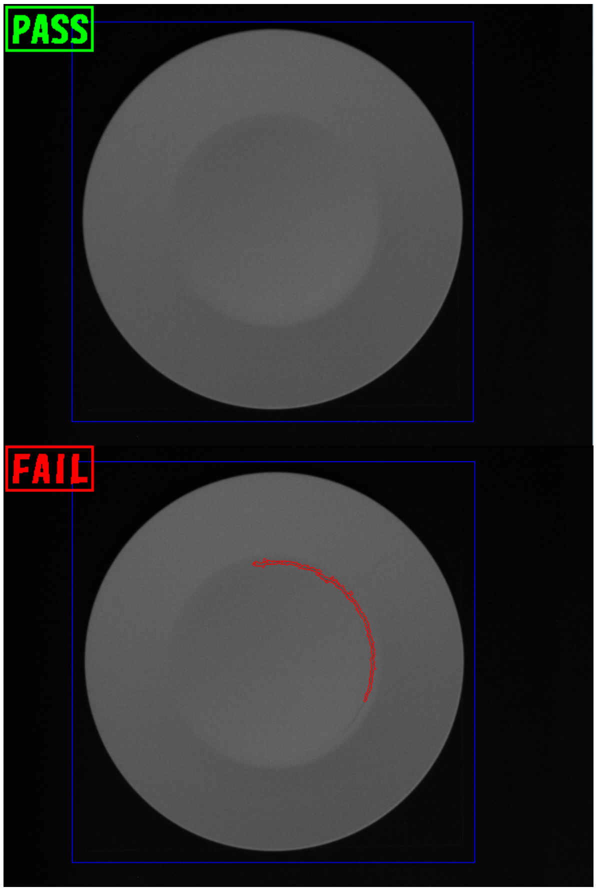

Fig. 4. Evaluation of plates surface defects. Top image: Passed inspection for surface defects. Bottom image: Failed inspection for surface defects.

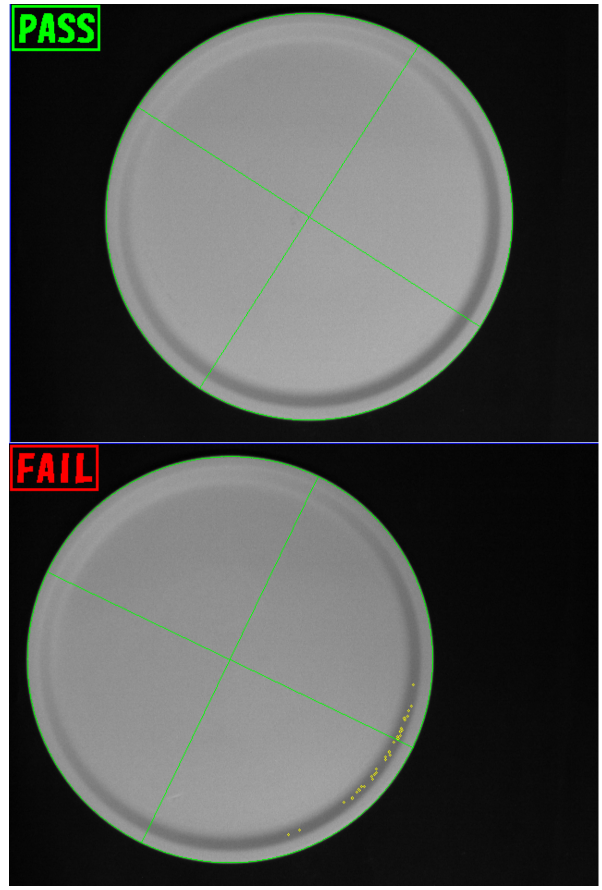

Fig. 5. Evaluating texture of plates. Top image: The target passes the inspection. Bottom image: The target fails the inspection.

position in the image, the Histogram tool to detect the cracks and the Surface flaw inspection tool was used to detect fissure on the surface of the plates.

A mask was used to mask the areas that are outside the plate's outline. It is advisable to use masks for cases where the background of the images is not smooth. After applying a mask, the instruments used only act on the surface of the plate.

For evaluate the inspection we created 2 variables and 2 conditions: one to evaluate the histogram result and one to evaluate the result of the Surface flaw inspection tool. To evaluate the histogram we used as the variable the "Minimum" value, which describes the brightness of the darkest pixel. The condition to check if a plate has cracks is: if the brightness value of the darkest pixel is greater than or equal to 20, then the target will pass the inspection.

To check if the plates have surface defects we used the number of defects as the variable returned by the Surface flaw inspection tool. The condition to evaluate if a plate has fissures is: if the number of defects identified is equal to 0, then the target passes the inspection, else the target fails the inspection.

The top image in Figure 6 shows the combined inspection of a plate without defects. The target passed the inspection because the two conditions were met. The middle image from Figure 6 shows a failed inspection because a fissure was detected on the surface of the plate, so the condition of the Surface flaw inspection was not met. The bottom image failed the inspection because the plate has a crack. Due to masking the image, the Histogram tool sees only the surface of the plate defined at the beginning of the inspection as a pattern. In the case of the plate from figure, there are more black pixels in the area where there is a crack. If the brightness value of a single black pixel is less than 20, then the target fails inspection. The brightness value of the darkest pixel in the figure is 14, so the condition is not met and the target fails inspection.

V. Conclusions

In this work we proposed a quality monitoring system based on computer vision for defect detection in porcelain industry. The architecture design, quality and principles of interconnection of products will lead to a simple and inexpensive quality control technology. Enhancing product quality, anticipating the defects before the final phase of sorting, packing or delivery will be ensured through intelligent visual control systems. The results of this system will have a positive economic impact for the companies involved in the porcelain industry.

We investigated if an image of a plate is correct or not using computer vision techniques. We used iRVision Inspec-

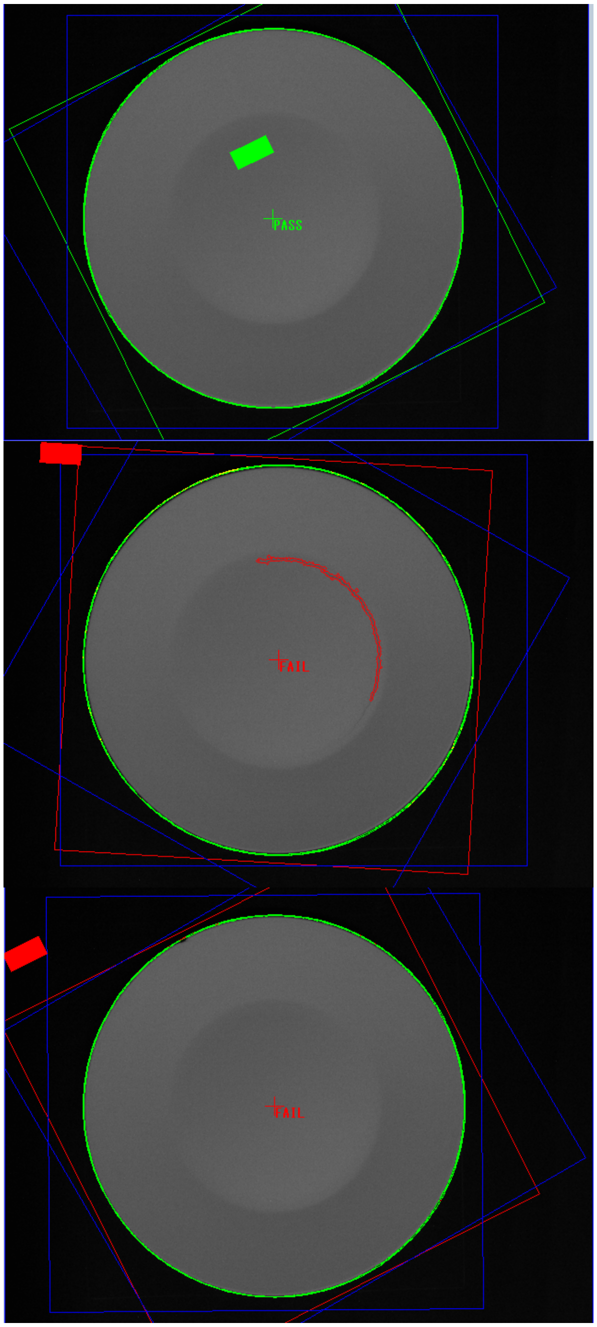

Fig. 6. Evaluation of plates surface and flaws defects. First image: Pass inspection. Second image: Fail inspection for surface defects. Third image: Fail inspection for cracks defects.

tion for evaluating images. iRVision Inspection has tools for inspections which successfully evaluate if a target image is defective or not. We investigated several iRVision Inspection tools for detecting surface defect, cracks and deformations and for texture defects. The experimental evaluation shows that the inspection system that we developed can correctly identify if a product is defective or not.

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