Statistical Pattern Modeling in Vision-Based Quality Control Systems

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Abstract. Machine vision technology improves productivity and quality management and provides a competitive advantage to industries that employ this technology. In this article, visual inspection and quality control theory are combined to develop a robust inspection system with manufacturing applications. The inspection process might be defined as the one used to determine if a given product fulfills a priori specifications, which are the quality standard. In the case of visual inspection, these specifications include the absence of defects, such as lack (or excess) of material, homogeneous visual aspect, required color, predetermined texture, etc. The characterization of the visual aspect of metallic surfaces is studied using quality control chars, which are a graphical technique used to compare on-line capabilities of a product with respect to these specifications. Original algorithms are proposed for implementation in automated visual inspection applications with on-line execution requirements. The proposed artificial vision method is a hybrid between the two usual methods of pattern comparison and theoretical decision. It incorporates quality control theory to statistically model the pattern for defect-free products. Specifically, individual control charts with 6-sigma limits are set so the inspection error is minimized. Experimental studies with metallic surfaces help demonstrate the efficacy and robustness of the proposed methodology.

Key words: quality control charts, automated visual inspection, image processing, statistical pattern recognition, steel surfaces.

1. Introduction

The inspection process is defined as [9] the one that is followed to decide whether a given product meets previously established specifications, which are defined as the quality standard. In the case of visual inspection, these specifications include the absence of defects such as lack of material, homogeneous visual aspect, required color, predetermined texture, etc. This process requires the use of images which include enough information about the visual appearance of the product to be inspected. It also requires a quick, reliable decision making step and a feedback loop to the manufacturing process. Besides traditional inspection in mass production with statistical methods, and with the aim of eliminating producer's and buyer's risks, sometimes it is necessary to perform a 100% check of production [19]: for example, in industries like ceramics, steel, automotive [3, 10], etc., due to competitive factors, or in industries like pharmaceuticals, aerospace, etc., due to critical factors [6].

The automation of visual inspection implies including in the systems a high degree of reasoning capacity in the decision making process or in the classification of the defects regarding its visual appearance, eliminating then the lack of homogeneity in the inspection results due to human factors, therefore increasing efficacy [17].

Visual inspection techniques are classified in two groups. The first one includes comparison-with-patterns techniques, that is, the defects are detected by comparing defect-free patterns with images of actual products. The second group relates to theoretic decisions, used to verify a set of characteristics of the product against those of an ideal product.

Comparison with a pattern. This technique is based on the comparison pixel by pixel of two images, one of the inspected product and another of the ideal product. This last one must include the visual model of the product to be studied. In the case of multilevel images, patterns must be carefully developed to assure that small defects are detected and not confounded with the inherent variability of the visual characteristics of the product and the errors in the measuring process [16]. This type of technique is sufficiently flexible, and sometimes is the only possible way to perform a reliable inspection. It has been used in the quality control of printed circuit boards [13], tiles [15], etc.

Theoretic inspection. This type of methods is based on the adequate parameterization of the defect-free product. This parameterization consists of a vector of image characteristics, like areas, perimeters, shapes, moments, textures, histograms, etc. It is necessary to develop a classifier which helps decide on the quality of the inspected product (based on rules and neural networks). This type of technique has been used in the quality control of metallic pieces [18], paper pulp [8, 12], textile seams [1], etc.

Inspection processes based on textures are included in this group. These are processes in which a visual pattern with a certain degree of uniformity is analyzed [2]. The texture allows for the representation of the properties of the product and the localization of the defects.

In this article, a methodology is presented for the identification of defects in metallic surfaces. The proposed method is a hybrid between the inspection with a pattern and the use of theoretic decisions, with the aim to diminish the influence of their disadvantages and to maximize their advantages.

The objective of this inspection process is to identify possible defects, specifically bumps and scratches, in metallic surfaces with a uniform degree of curvature, as depicted in Figure 1. The detection of defects is to be done in the manufacturing process, right before the surface is painted.

The proposed methodology studies the characterization of the visual aspect of metallic surfaces using statistical techniques. Original algorithms have been devel-

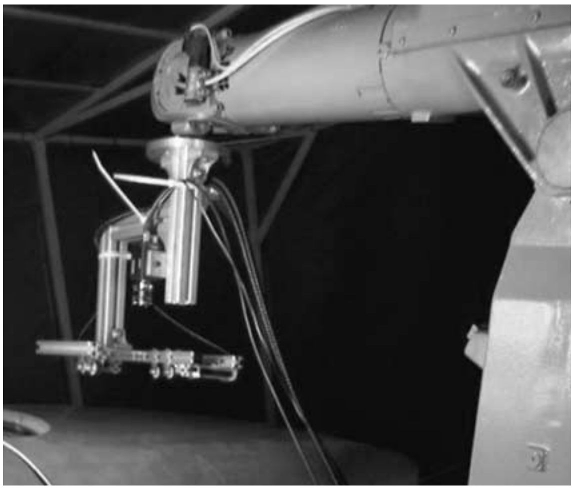

Figure 1. Inspection process.

oped for implementation in visual inspection applications with on-line execution requirements.

2. Def nition of the Problem

Choosing the illumination system constitutes one of the fundamental steps in any visual inspection system [3, 10], as it is used to pinpoint the undesirable characteristics that must be detected during inspection. Therefore, the illumination system is to possess a very good spatial and temporal uniformity.

The illumination system is crucial when dealing with surfaces which are very ref ective and have a plain texture, as in the case of metallic surfaces. The defects related to ref ection are of superf cial nature whereas the ones related to texture are due to design requirements.

For the detection of both defects, it is essential to optimally locate the sources of light and the video camera. Only if the object is correctly illuminated, errors like changes in tone or contrast might be avoided.

The light that gets to the object should provide constant intensity levels over the whole image. Whenever it is necessary to point out microstructure alterations of the surface, the illumination system is to guarantee, besides uniformity, the correct orientation of the incident light. In these cases, the camera must capture the specular component of the ref ected light. This component is different from the diffused light in terms of the intensity levels and the orientation of incident light.

In large objects, where directional illumination of great intensity is used, the area that is close to the source of light shows a higher level of gray than those that are further away, as shown in Figure 2.

In Figure 2, the light distribution is not uniform. The proposed algorithm models the characterization of the visual aspect using statistical techniques. The texture

Figure 2. Directional illumination in metallic surfaces.

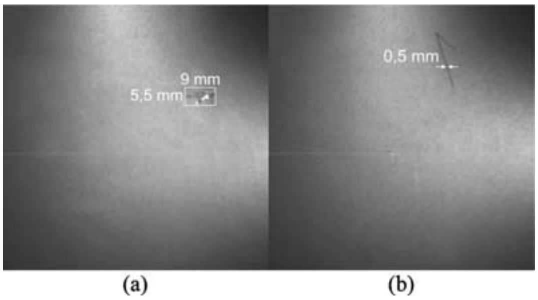

Figure 3. Defects in the metallic surface.

of the surface has been modeled with gaussian distributions using sequences of defect-free images. The algorithm allows for alterations in the microstructure of the surface in terms of the changes in the angles of ref ection of the rays of light coming from the source of illumination, with relation to the predef ned pattern. The model includes the effect of the noise associated to the transmission of the signal and to the source of light used.

Figure 3 depicts two different defects. In Figure 3(a), the plate has a small bump which induces deformations in its structure within 9×5.5 mm, whereas in Figure 3(b), a scratch of approximately 0.5 mm is shown.

3. The Proposed Algorithm

The algorithm is used to determine if the product meets specif cations or defects are found on its surface. It is based on the development of useful patterns that represent defect-free products, patterns which are used to statistically determine the quality of the product.

The original idea of this article is to combine visual inspection with quality control techniques that are commonly used in on-line inspection of manufacturing systems. Usually, quality control charts are used by operators to monitor performance characteristics, that are measured by traditional methods (gages, weight scale, etc.). In vision systems, the characteristics are incorporated into the charts by automatically converting an image into a measurable value (gray scale). On-line inspection is then more f exible and robust.

A posterior image processing step has also been developed to correctly determine the location of the defect, if it has been pinpointed by the control charts.

3.1. STATISTICAL PATTERN MODELING

The model is based on quality control theory, more specif cally, on quality control charts. The philosophy behind the charts is equivalent to the philosophy used to process images with inspection purposes. Pixels will be acceptable as long as their gray level stays within certain acceptable limits. Statistics allows for a robust design of these quality control limits so inspection errors are minimized.

3.1.1. *Development of Quality Control Charts*

QC charts are used to monitor the quality of a given process over time, both in terms of its mean behavior and its variability. They are simple graphical tools that depict a time series which shows the evolution of a variable. The value of this variable is obtained by sampling directly from the manufacturing process.

Their objective is to determine if the process is in statistical control, that is, if the mean value of the variable and its variation continue to lie within certain boundaries, called control limits. If the process is in control, it is said that the variability of the results is due to normal causes, whereas if the process is out of control, the variability is due to special, assignable causes.

A QC chart has the structure shown in Figure 4.

The values included in the chart are samples from the variable under study over time. The center line shows the mean value of the variable, whereas the upper control limit (UCL) and the lower control limit (LCL) are the limiting values of

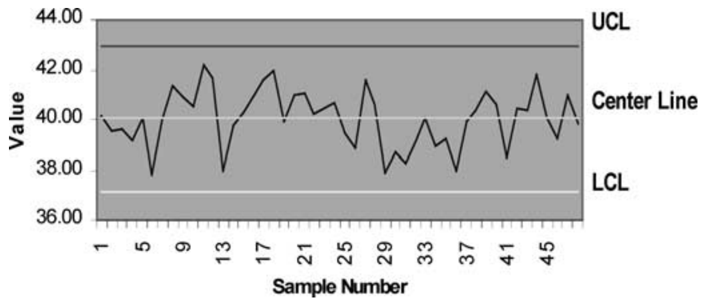

Figure 4. Control chart.

what constitutes normal behavior. (The assumption underlying the construction of the control chart is that the process is normally distributed.)

To create the chart, an initial sample of at least 20 values is necessary (preferably more than 30). The mean and standard deviation of the sample are calculated. The center line is equal to the mean of the variable. The limits are calculated as the center line plus or minus k standard deviations of the variable (usually $k = 3$).

3.1.2. *Types of Quality Control Charts*

There exist different charts depending on the nature of the data to be included in the chart and the nature of the process that generates the data. This data might be a variable or an attribute. For example, the length of a nail or the tensile strength of a rod fall in the f rst type, a continuous measurable value. The percentage of defective items or the count of defects per unit are examples of the second type. The process might be a batch process, which produces several comparable units at a particular point in time, or a continuous process, which generates one-at-a-time samples.

In the case of computer vision, a picture composed of pixels is obtained from a f at surface and the measure in a gray scale is obtained. One, and only one observation is taken from an object at a particular time, and the gray value obtained per pixel is a number between 0 and 255. Therefore, the control chart that applies to a vision system is a variables chart.

When dealing with variables, the two possibilities that are preferably used are [7]:

- $\overline{\mathrm{X}}/\mathrm{R}$ charts: a pair of charts in which the mean behavior is studied with the $\overline{\mathrm{X}}$ chart and the variability with the R chart (R for range). The values included in the $\overline{\mathrm{X}}$ chart are the mean values of samples of n identical items. In the R chart, the ranges (maximum–minimum) are recorded.
- I/MR charts: a pair of charts in which the mean behavior is studied with the I chart (I for individuals) and the variability with the MR chart (MR for moving range). The values included in the I chart are direct values of a sample of the item, which is unique. In the MR chart, the ranges between consecutive samples are recorded.

Since only individual pictures are taken of the surface, the pair of control charts that apply to the automated inspection system presented in this article is the I/MR charts.

Two further comments on how to apply the pair of charts are necessary at this point [11]. First, the data to be included in the I chart must be checked for normality prior to the study. Second, there exists the possibility of committing inspection errors. The following two sections analyze in detail these comments.

3.1.3. *Test for Normality*

One of the assumptions included in control chart theory is that the underlying variable distribution is normal. The charts in which the values recorded are mean values do not need further checking for normality since the Central Limit Theorem applies as soon as 20 samples are used to construct the charts (for example, the $\overline{\mathrm{X}}$ chart). However, the I chart records observation values, so a prior check for normality is required.

The test of hypothesis for normality is:

H_0: data follow a normal distribution,
H_1: data do not follow a normal distribution.

The result of performing the test is a p-value which determines the signif cance level at which H_0 is rejected. If the required signif cance level is less than the calculated p-value, H_0 is not rejected, whereas if the level is greater than the p-value, H_0 is rejected. Usual signif cance levels for a single test are 0.05 and 0.01 (95 and 99% conf dence).

The Anderson–Darling test [5] is one of the more powerful tests for normality found in the literature for small samples (the test is valid for $n \geqslant 8$ and calculates a statistic called A^2).

3.1.4. *Sampling Errors*

By using control charts there exists the possibility of committing sampling errors, both of rejecting good products and accepting bad ones. Let us quantify these important possible errors, which are directly related to the chosen value of k (distance at which the control limits are set, measured in standard deviations).

Errors per chart. The primary error that results from the use of a chart in each sample is the possibility of determining that the process has gone out of control when indeed the process remains in control. This error is usually called α. It is the probability that the new sample falls outside the limits if the process stays in control, so its value is

$$\alpha = \Pr(z > |k\sigma|) = 2\Pr(z > k\sigma)$$

where z is the standard normal distribution, which is included in tabular form in statistics textbooks. It is assumed that the variables included in the graph follow this distribution, as the normal causes or white noise also follow the normal or gaussian distribution. For example, if $k = 3$, the required error is $\alpha = 0.27\%$.

The other possible error, called β, is the probability that the process stays stable when indeed is out of control. Its calculation is more complex, as it is necessary to know the new normal distribution that the process follows.

The size of the errors varies in opposite directions. As k increases, α decreases while β increases.

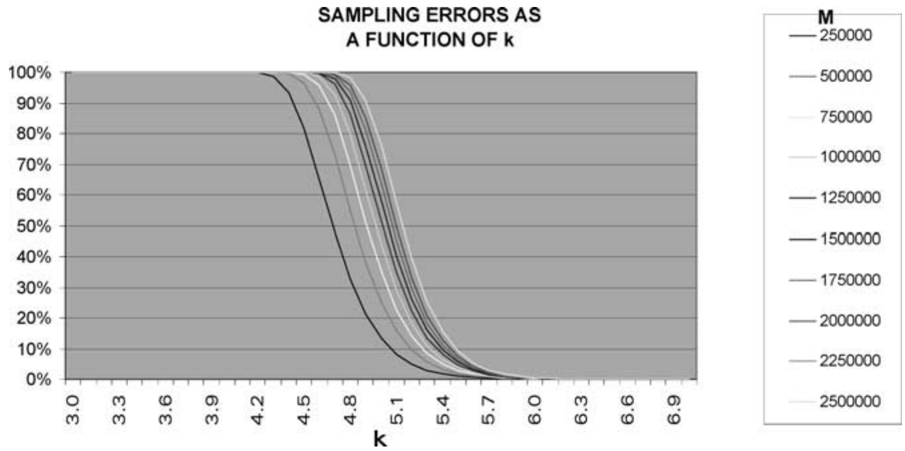

Figure 5. Relationship between k and the sampling error.

Errors per study (multiple charts). If M variables are being monitored in parallel, the total error is a function of the individual errors on each variable. If the charts are considered independent, the total error is calculated as follows:

$$\text{Error} = 100\big[1 - (1-\alpha)^M\big] = 100\big[1 - (1 - 2\,\Pr(z > k\sigma))^M\big].$$

The following graph (Figure 5) shows the relationship between the scalar k (number of standard deviations used in the chart) and the sampling error, for various levels of M, ranging from 512×512 to 1024×1024 pixels (current best precision) and beyond.

For the total error to be less than 10%, k must be at least 5. If $k = 6$, the error vanishes for any M.

3.1.5. *Pattern Model*

The pattern is therefore an image made of M pixels, each with its QC limits, with the values measured in the gray scale. To calculate the acceptance limits, a signif cant number of images ($\geqslant$20) are taken of error-free metallic surfaces. Values for the mean and the standard deviation for each pixel are calculated. Then the limits are set at the mean value plus or minus k standard deviations. Since the total number of charts is M, to reduce the possibility of committing an α error the choice of k is 6.

3.2. ON-LINE INSPECTION

The algorithm must convert the image obtained with the video camera and compare it with the given pattern. Defects should be found with accuracy and located in the metallic surface.

3.2.1. *Assigning Values to Pixels*

For a given surface, images are obtained with a video camera [4]. The images are divided into pixels, each of which is assigned a value in the gray scale. These values, however, might be distorted depending on the positioning of the robot. A transformation of the gray values should be performed in the case of a f aw in the source of light or the positioning of the camera.

The algorithm incorporates a step to check for adequate illumination and performs a shift in the value if necessary. An adaptive process based on window analysis has been developed. For a given window, the difference between the value of the pattern and the processed image is calculated, for each pixel included in the window. The distribution of the differences is assumed to be normally distributed and estimated by estimating its mean value and standard deviation. If no abnormal individual difference is found, a shift is perform by moving the value of each pixel of the inspected image by a f xed amount, which is the difference in the mean value for each window. If, on the other hand, any of the differences is too large, the shift is not performed and the abnormal value stays for posterior checks to pinpoint.

The algorithm is the following:

1. Select a window with P pixels
2. For any pixel p:
   Calculate x_p: value of gray for the pixel in the pattern
   Calculate y_p: value of gray for the pixel in the inspected image
   Calculate the difference between the two readings:

   $$z_p = x_p - y_p$$

3. Calculate $\overline{z}$, σ_z
4. Calculate the conf dence interval on the difference

   $$(\overline{z} - k\sigma_z,\ \overline{z} + k\sigma_z)$$

5. For any pixel p, calculate D:
   If z_p within the conf dence limits

   $$D_p = 0$$

   Else

   $$D_p = 1$$

6. Perform the adjustment:
   If every $D_p = 0$
   Perform the shift and calculate y'_p

   $$y'_p = y_p + \overline{z}$$

   Else
   Do not perform the shift.

Table I shows the application of the algorithm to the inspection system, for an 8×8 window, with the calculations performed in a MSExcel spreadsheet.

Table I. Adjustment for illumination

								Mean	STD
			x						
162.0	158.8	158.9	156.0	153.6	153.4	152.6	151.8		
161.0	156.7	155.2	152.4	150.2	150.0	150.2	151.1		
157.7	155.0	151.5	149.1	147.5	146.1	147.5	149.3		
154.7	153.1	150.7	147.3	145.9	144.4	145.9	147.4		
153.5	151.5	151.2	147.0	145.5	142.8	144.2	144.1		
152.5	150.9	152.0	146.7	144.8	142.2	142.1	140.8		
150.7	149.1	150.5	143.9	142.0	140.1	139.1	137.1		
148.4	147.0	147.1	141.6	140.1	139.9	140.2	139.5	148.67	5.76
			y						
144.0	143.0	143.0	143.0	143.0	143.0	143.0	146.0		
144.0	143.0	141.0	144.0	142.0	143.0	141.0	144.0		
145.0	141.0	143.0	141.0	142.0	141.0	143.0	142.0		
142.0	141.0	143.0	141.0	142.0	141.0	143.0	144.0		
142.0	143.0	141.0	142.0	141.0	141.0	141.0	143.0		
143.0	143.0	143.0	143.0	142.0	142.0	141.0	141.0		
143.0	141.0	145.0	141.0	143.0	141.0	141.0	141.0		
142.0	140.0	143.0	142.0	143.0	139.0	142.0	142.0	142.28	1.28
			z						
18.0	15.8	15.9	13.0	10.6	10.4	9.6	5.8		
17.0	13.7	14.2	8.4	8.2	7.0	9.2	7.1		
12.7	14.0	8.5	8.1	5.5	5.1	4.5	7.3		
12.7	12.1	7.7	6.3	3.9	3.4	2.9	3.4		
11.5	8.5	10.2	5.0	4.5	1.8	3.2	1.1		
9.5	7.9	9.0	3.7	2.8	0.2	1.1	−0.2		
7.7	8.1	5.5	2.9	−1.0	−0.9	−1.9	−3.9		
6.4	7.0	4.1	−0.4	−2.9	0.9	−1.8	−2.5	6.39	5.26
								Conf dence limits	
							k	−6	6
								−25.14	37.92
			D						
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	SHIFT	

Table I. (Continued)

			y'						
150.39	149.39	149.39	149.39	149.39	149.39	149.39	152.39		
150.39	149.39	147.39	150.39	148.39	149.39	147.39	150.39		
151.39	147.39	149.39	147.39	148.39	147.39	149.39	148.39		
148.39	147.39	149.39	147.39	148.39	147.39	149.39	150.39		
148.39	149.39	147.39	148.39	147.39	147.39	147.39	149.39		
149.39	149.39	149.39	149.39	148.39	148.39	147.39	147.39		
149.39	147.39	151.39	147.39	149.39	147.39	147.39	147.39		
148.39	146.39	149.39	148.39	149.39	145.39	148.39	148.39	148.67	1.28

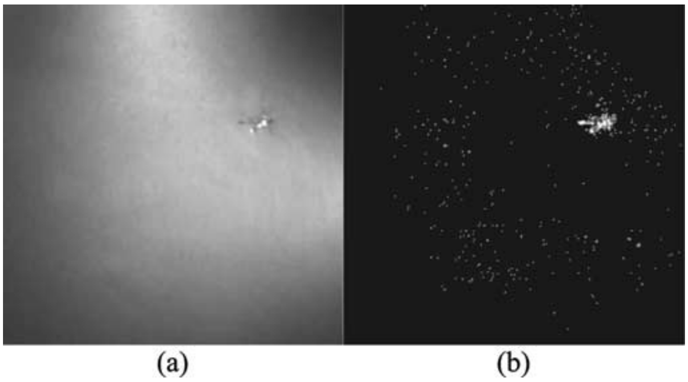

Figure 6. Processing of the image.

3.2.2. *Processing of the Image*

Figure 6(a) shows the image taken from the metallic surface after applying the adjustment for illumination. Figure 6(b) shows the result of comparing Figure 6(a) pixel by pixel with the pattern and its corresponding control limits established with 6 standard deviations. In Figure 6(b) black pixels are those whose gray level is within the control limits, whereas white pixels are those whose gray level is outside the control limits.

The defect is clearly identif ed, but also isolated white pixels appear all over the processed image. The existence of the latter is due to dust particles that are included in the surface, which are almost unavoidable. The purpose of this processing step is to differentiate between the isolated pixels and the ones that correspond to defects.

To eliminate these isolated pixels, a morphologic f ltering step is carried out over the whole domain [14], with the following kernel:

0	1	0
1	0	1
0	1	0

.

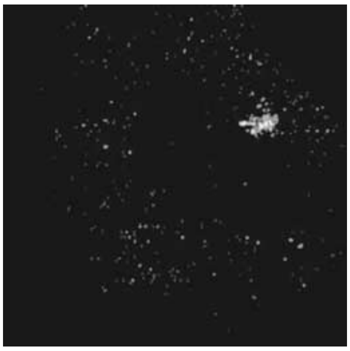

Figure 7. Application of the kernel.

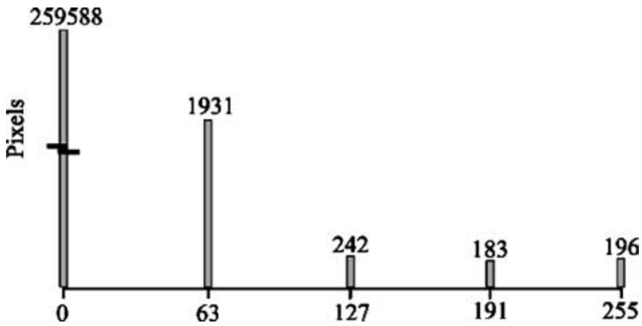

Figure 8. Levels of gray.

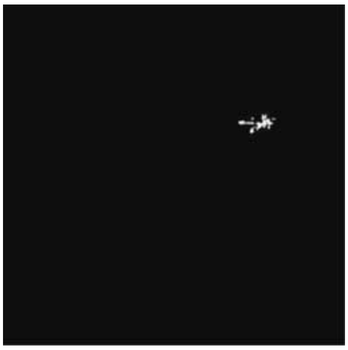

Figure 9. Image after threshold.

With this kernel, the number of neighbors is analyzed considering that the signaled pixels will show no more than two neighbors, whereas pixels with real defects will have at least three neighbors. The result of the processing step is shown in Figure 7.

Figure 8 shows the histogram resulting from counting the pixels of Figure 7. Five levels of gray are clearly shown, corresponding with the different number of neighbors.

Figure 9 shows the image after applying the threshold of 3 or more neighbors to Figure 7.

Finally, the white pixels are grouped and labeled to identify the defect. This defect is located with respect to the surface coordinates, also indicating its area, length and height.

4. Experimental Results

The algorithm has been tested in a real situation. Several steel surfaces are tested to look for bumps and scratches during the manufacturing process of metallic pieces.

The inspection system. The artif cial vision system is composed of a progressive scan CCD camera which covers in each frame an area of 20 $\times$ 15 cm, and an illumination system of continuous current. The light gets to the surface via two optic f ber connecters which are located perpendicularly to each other in the same plane. The optic axis of the CCD camera is perpendicular to the plane of light, as shown in Figure 10.

The system has been implemented using an Asea IRB 2400 robot, to facilitate the inspection process. The inspection velocity of the robot is 200 mm/s.

To create the quality charts, twenty images are taken of f at surfaces without defects. Each image is composed of 768 $\times$ 572 pixels, so $M = 439296$ total pixels. A minimum value of 6 standard deviations is needed ($k = 6$) to almost vanish the inspection errors. The test for normality has been successful for different series of twenty images.

Detection of bumps and scratches. Figures 11 and 12 include the video image and the processed images of different defects that have been detected in the metallic surface. There is a series of three images for each defect: the f rst one is the image as seen by the video camera after applying the adjustment for illumination, the second one shows the processed image after performing the control charts check, and f nally, the third one depicts the processed image after the f ltering step.

The system has been so far designed to analyze surfaces with small curvature variations. For different curvatures, the predetermined patterns are different in the

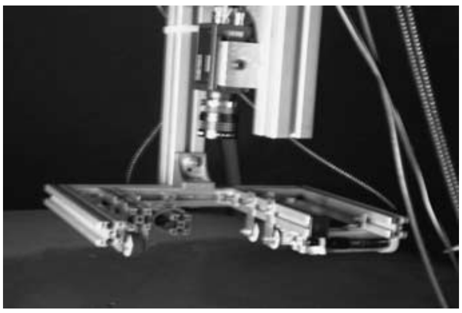

Figure 10. Artif cial vision system.

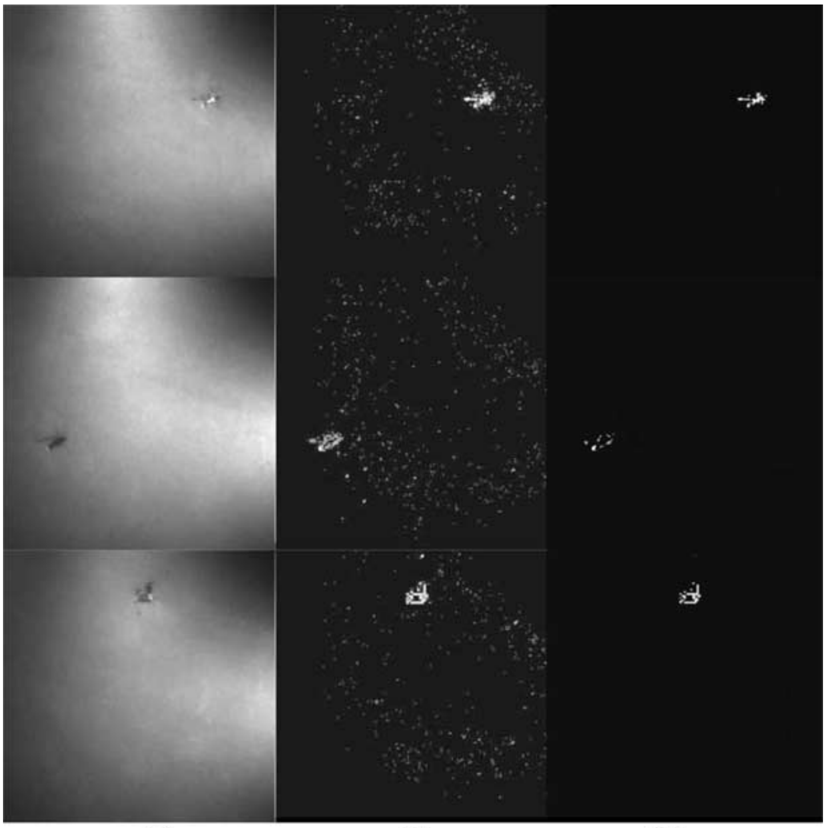

Figure 11. Processing of bumps.

same surface, eliminating the possibility of controlling any type of surface. However, the proposed system can handle small variations, like the one presented in Figure 13.

5. Conclusions

Machine vision provides innovative solutions in the direction of industrial automation. An algorithm has been developed for on-line inspection of metallic surfaces using both artif cial vision techniques and quality control charts. The combination of the techniques in a robust robotic system has proven to be successful in an automated visual inspection application.

On-line images are compared with defect-free surfaces via predef ned patterns, which have been developed combining theoretical behavior and statistical comparisons. Quality control charts, with 6 sigma philosophy, are used to monitor the search for bumps and scratches in manufacturing processes. The possible er-

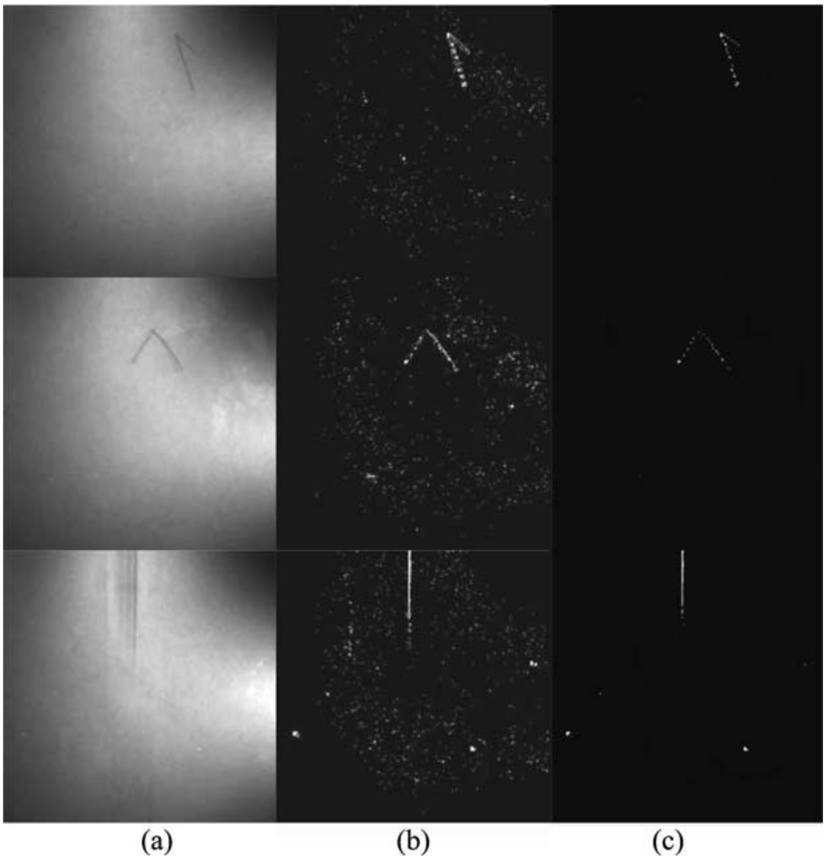

Figure 12. Processing of scratches.

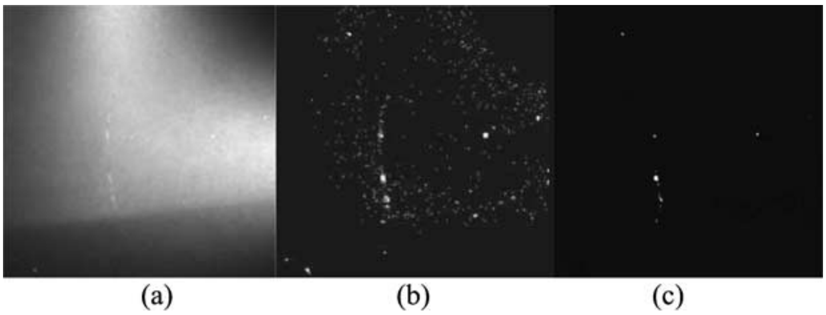

Figure 13. Images of curve images.

rors introduced by the misplacement of the robotic system are eliminated using a statistical illumination adjustment.

Experimental results show that the proposed automated inspection system is suff ciently robust and reliable to be applied in different manufacturing environments.

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