Surface defect detection of 3D objects using robot vision

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Abstract
Purpose – The purpose of this paper is to develop a robot vision system for surface defect detection of 3D objects. It aims at the ill-defined qualitative items such as stains and scratches.
Design/methodology/approach – A robot vision system for surface defect detection may counter: high surface reflection at some viewing angles; and no reference markers in any sensed images for matching. A filtering process is used to separate the illumination and reflection components of an image. An automatic marker-selection process and a template-matching method are then proposed for image registration and anomaly detection in reflection-free images.
Findings – Tests were performed on a variety of hand-held electronic devices such as cellular phones. Experimental results show that the proposed system can reliably avoid reflection surfaces and effectively identify small local defects on the surfaces in different viewing angles.
Practical implications – The results have practical implications for industrial objects with arbitrary surfaces.
Originality/value – Traditional visual inspection systems mainly work for two-dimensional planar surfaces such as printed circuit boards and wafers. The proposed system can find the viewing angles with minimum surface reflection and detect small local defects under image misalignment for three-dimensional objects.

Keywords Robotics, Electronic equipment and components, Surface defects, Sensors

Paper type Research paper

1. Introduction
Non-contact visual inspection based on image analysis techniques has become important for qualitative evaluation of surface quality in manufacturing. Defects that appear as local anomalies, such as stains, scratches and wear, on material/product surfaces generally lack quantitative measures to define. They are also difficult to identify if the surrounding background contains complex patterns.

Automated visual inspection has been successfully applied to a wide variety of material surfaces found in industry, such as printed circuit boards (PCBs) (Mogant and Ercal, 1996; Yeh and Tsai, 2001; Leta et al., 2008), semiconductor wafers (Su et al., 2002; Shankara and Zhongb, 2005; Yeh et al., 2010), liquid crystal display panels (Oh et al., 2004; Zhang and Zhang, 2005; Tsai and Tsai, 2010), solar cells (Ordaz and Lush, 2000; Fu et al., 2004; Tsai et al., 2010) and textile fabrics (Cho et al., 2005; Kumar, 2008; Xie, 2008). For PCB inspection, embedded fiducial markers on the boards allow the image under inspection to be registered with respect to the golden template for comparison. For semiconductor wafer inspection, the surface shows repetitive die patterns in the image so that the defect can be identified when it breaks the periodicity on the surface. The visual inspection tasks for material surfaces mentioned above can be carried out with one single view of the camera. That is, all these industrial products can be treated as two-dimensional (2D) planar surfaces and, therefore, the inspection task can be completed in a 2D image.

Very recently, high-end hand-held electronic devices such as cellular phones and digital cameras demand high surface quality of the end products before they can be shipped to customers. Any appearance defects may degrade the value of the products. The hand-held devices are, by necessity, three-dimensional (3D) objects, and traditional visual inspection systems based on one single view cannot be applied to surface defect detection of 3D objects. The existing visual inspection systems for 3D objects mainly focus on dimension measurements using multiple views of fixed cameras or a flexible camera mounted on a robot arm (Neto and Nehmzow, 2007; Heizmann, 2009; Sattar and Brenner, 2009). The focus is on the geometric measurements of the 3D object, not on the qualitative properties of the object surfaces.

In this paper, we propose a robot vision system for surface defect detection of 3D objects, with a specific aim toward hand-held electronic devices. The sensing camera is mounted
on the end-effector of a robot arm. It allows the 3D object under inspection to be flexibly observed from different angles and enables all surfaces of interest to be evaluated. Since the target products to be inspected may contain separate uniform (non-textured), textured, and patterned surfaces, the image of each viewing angle of a defect-free object is first taken and stored as a template for comparison. For each new object under testing, the same views are repeated by the robot, and each sensed image is compared to the corresponding template image. A template-matching technique is then used to identify local defects in the two compared images at each viewing angle.

Application of the robot vision system for surface defect detection of 3D objects raises two main problems to overcome:

1. The cases of the high-end electronic devices are generally made of metallic or plastic materials with very smooth surfaces. They can be highly reflective on the surface at some viewing angles. The reflection region in the image could be falsely detected as a local defect, or the reflection may conceal a defect on the surface, resulting in mis-detection.

2. Unlike the PCBs, the final appearance of an electronic product does not have embedded fiducial markers for image registration. The image taken from an individual viewing angle by the robot in a repetitive process may present displacement with respect to the template image.

In this study, we first propose a reflection-detection process to identify the presence/absence of reflection in an image so that the reflection-free viewing angle of the camera-equipped robot can be automatically determined. Second, an automatic marker-selection process for each individual image of a defect-free reference object is presented for image registration, and then a template-matching algorithm that is tolerant of displacement between two compared images is proposed to detect local anomalies. All these efforts make the robot vision system practical for surface defect detection of 3D objects.

The paper is organized as follows: Section 2 describes the configuration of the robot vision system. Section 3 introduces the view planning and reflection detection in images. Section 4 presents the automatic marker-selection and template-matching processes for defect detection. Section 5 discusses the experimental results. Various hand-held devices are used to evaluate the efficacy and feasibility of the proposed vision inspection system. Section 6 concludes the paper.

2. System configuration

The robot vision system in our work is implemented on the Denso robot (model VS-6556G). It is a six-axis articulated robot with a repeatability of $\pm 0.02$ mm. The charge-coupled device camera is mounted on the end-effector of the robot. A ring-shaped light-emitting diode (LED) with a diffusion dome is used as the light source. The ring light casts light from all directions to create more uniform and shadow-free illumination. The diffuse dome light further reduces specular reflections on the object surface. The LED dome light is directly attached to the camera so that it can move along with the robot arm. The image taken by the camera is 1,600 $\times$ 1,200 pixels in size with 8-bit gray levels. Figure 1 shows the configuration of the robot vision system implemented in this study.

3. View planning and reflection detection

View planning for reconstruction and inspection of 3D objects with multiple viewing angles has been extensively studied over the past two decades (Willam et al., 2003; Chen and Li, 2002, 2004; Munkelt et al., 2009). The objective of view planning of a robot path is to find the minimum number of images from different viewing angles that will cover all the required surfaces to reconstruct/inspect the entire 3D object. The inspection task in view planning is quantitative measurements of geometric dimensions. It generally assumes the object to be modeled is enclosed by a spherical shell.

The view planning is widely based on the next best view (NBV) (Wong et al., 1998), which determines a new sensor position that gives the largest unseen area of the object. The optimality criterion of view planning is mainly based on total visible edge length or total surface area (Shin and Gerhardt, 2006). It ignores the possibility that the image obtained from the NBV may show severe reflection on the surface. The proposed reflection-detection algorithm in this paper can be used as a constraint in the view planning model. View planning can thus find a minimum number of required views without showing reflections in all selected images. However, since detailed view planning is beyond the scope of this study, we focus on reflection detection for qualitative inspection of 3D object surfaces.

Since the target objects to be inspected in this study are small hand-held devices with simple curved surfaces, we implement a straightforward form of view planning to obtain the required views for our robot vision system. It is also assumed that the 3D object is enclosed in a sphere. All the surfaces of a hand-held product can be observed from top views, front and rear views, and right- and left-side views. We therefore need only two orthogonal scan trajectories along the spherical shell to obtain the required viewing angles.

Let the optical-axis of the end-effector-mounted camera be perpendicular to the table surface and point to the center of the object in the straight top-view image. Denote by $B(x, y)$ the binary image of the top-view image of size $M \times N$ with...
$B(x,y) = 1$ for object points and 0 for background points. The object to be inspected can be placed on a high-contrast background, and a simple automatic binary thresholding technique such as Otsu’s method (Gonzalez and Woods, 1992) can be applied to segment the gray-level image into a binary image. The center is then given by:

$$\bar{x} = \frac{\sum \sum x \cdot B(x,y)}{\sum \sum B(x,y)}$$

$$\bar{y} = \frac{\sum \sum y \cdot B(x,y)}{\sum \sum B(x,y)}$$

The two orthogonal directions of the object in the 2D top-view image can be derived from the principal component analysis. Let $M$ be the covariance matrix of the object in the top-view image, and:

$$M = \begin{bmatrix} m_{xx} & m_{xy} \\ m_{xy} & m_{yy} \end{bmatrix}$$

where:

$$m_{xx} = \frac{1}{\sum \sum B(x,y)} \left( \sum \sum x^2 \cdot B(x,y) \right) - \bar{x}^2$$

$$m_{xy} = \frac{1}{\sum \sum B(x,y)} \left( \sum \sum x \cdot y \cdot B(x,y) \right) - \bar{x} \cdot \bar{y}$$

$$m_{yy} = \frac{1}{\sum \sum B(x,y)} \left( \sum \sum y^2 \cdot B(x,y) \right) - \bar{y}^2$$

The eigenvectors $e_1$ and $e_2$ of the covariance matrix $M$ give the two scan directions of the orthogonal trajectories in the view sphere. Figure 2 shows the view sphere and the orthogonal scan trajectories of the robot vision system.

For a given viewing angle in the scan trajectory, we need to detect the presence/absence of surface reflection in the sensed image. Any views that produce substantial reflection in the image must be discarded, since they show no surface information in the reflection regions. Detection of a reflection region in the image is no trivial task. One cannot simply use a thresholding technique and identify white pixels as parts of the reflection region in the image. For hand-held electronic devices with fine metallic or plastic cases, reflections on the object surfaces depend highly on the sensing and lighting angles of the end-effector-mounted camera and light source.

Let the viewing angle of the camera be defined as the angle between the optical-axis of the camera and the table surface. The inclined angle is measured clockwise from the table surface and is thus, between 0° and 180°. Figure 3(a) and (b) shows the images of a battery charger at the viewing angles of 80° and 98°, respectively. Owing to the curved surface of the object, the surface is highly reflective. In Figure 3(a), the reflection region conceals the printed characters and may cause false alarms. In contrast, when the viewing angle of the camera is inclined from 80° to 98°, as shown in Figure 3(b), the reflection region is shifted from the left to the right of the object and the scratch defect is not visible in the image. In Figure 3(c), the surface details of the printed characters and the scratch defect are well present with minimum reflection when the viewing angle of the camera is set at 121°.

For a given image at a specific viewing angle, the observed image intensity at a pixel location $(x, y)$ is generated by incoming illumination and is reflected by the surface of the object. The observed image $f(x,y)$ can thus be modeled as the product of the illumination $f_i(x,y)$ from the light source and the reflection $f_r(x,y)$ of the object surface (Phong, 1975), i.e.:

$$f(x,y) = f_i(x,y) \cdot f_r(x,y)$$

**Figure 3** Battery charger images with light reflections at different viewing angles

Notes: (a) Image at viewing angle 80°, with the printed characters concealed; (b) image at viewing angle 98°, with the scratch concealed; (c) image at viewing angle 121°, with all surface details visible
Assuming the scene illumination component \( f_i(x, y) \) varies slowly over space and the reflection component \( f_r(x, y) \) contains high-frequency details, a homomorphic filter (Moloney, 1991; Toth et al., 2000; Radke et al., 2005) can be used to separate the two components of the observed image. By taking the logarithm on both sides of the model in equation (2), we obtain:

\[
\ln [f(x, y)] = \ln [f_i(x, y)] + \ln [f_r(x, y)]
\]

(3)

The image becomes additive in the log-transform space. The low-frequency illumination component can then be separated by a low-pass filter, i.e.:

\[
\ln [f_i(x, y)] = \text{LP} \{ \ln [f(x, y)] \}
\]

(4)

and the reflection component is given by:

\[
\ln [f_r(x, y)] = \ln [f(x, y)] - \text{LP} \{ \ln [f(x, y)] \}
\]

(5)

where \( \text{LP} \{ \cdot \} \) is a Gaussian low-pass filter on the sensed image \( f(x, y) \). In this study, a Gaussian filter of size 11 \( \times \) 11 with scale parameter \( \sigma = 2 \) is used for low-pass filtering, i.e.:

\[
\text{LP} \{ \ln [f(x, y)] \} = \sum_i \sum_j \ln [f(x + i, y + j)]
\]

\[
\cdot \exp \left[ -\frac{i^2 + j^2}{2\sigma^2} \right]
\]

The final reflection image can thus be estimated by:

\[
f_r(x, y) = \exp [\ln [f_r(x, y)]]
\]

(7)

The reflection region in the sensed image is detected from the difference between the original image \( f(x, y) \) and the estimated reflection image \( f_r(x, y) \). That is:

\[
\Delta f(x, y) = |f(x, y) - f_r(x, y)|
\]

(8)

Since the reconstructed image \( f_r(x, y) \) may have an intensity scale different from that of \( f(x, y) \), a simple statistical control limit is used to set up the threshold for segmenting the reflection pixels in the resulting difference image \( \Delta f(x, y) \). The reflection threshold is given by:

\[
T_{\Delta f} = \mu_{\Delta f} + K \cdot \sigma_{\Delta f}
\]

(9)

where \( \mu_{\Delta f} \) and \( \sigma_{\Delta f} \) are the mean and standard deviation of the whole difference image of size \( M \times N \), i.e.:

\[
\mu_{\Delta f} = \frac{1}{MN} \sum_x \sum_y \Delta f(x, y)
\]

\[
\sigma_{\Delta f} = \left( \frac{1}{MN} \sum_x \sum_y (\Delta f(x, y) - \mu_{\Delta f})^2 \right)^{1/2}
\]

4. Image registration and template matching

A hand-held device may present various surfaces on the cases, such as uniform/non-textured, textured, patterned and printed character regions. A template-matching technique that compares the similarity (or dissimilarity) between the defect-free template image and the scene image under test is possibly the only way to detect defects in a complex surface containing patterns or shaped figures. To apply template matching for defect detection, the two compared images must be accurately registered.

The robot arm can position repeatedly the end-effector-mounted camera to each viewing angle trained from the defect-free template object. The repeatability of the robot and positioning of the object on the table may result in minor displacement between the template image and the test image at a given viewing angle. The appearance of a final product does not have fiducial markers on each sensed image of the 3D object for registration. Therefore, we first propose an automatic marker-selection process to determine the most distinguishable markers for each template image at a given viewing angle, and then present a template-matching method to find local anomalies between the template image and the registered test image.

4.1 Marker selection and image registration

To find the translation and rotational angle between two images, we need at least two markers in each template image. We first divide the template image at a given viewing angle into four equal subimages and choose one marker for each subimage. The four markers should represent the richest and most unique features in the individual subimages. Therefore, we select the window with the maximum local gradient in each subimage as the marker. In this study, the window size of the marker is 200 \( \times \) 200 pixels. The selected markers will be used afterward to match the instances of the markers in the test image.

The gradient quantifies the changes of gray levels between neighboring pixels. We apply a simple 2 \( \times \) 2 edge operator to calculate the gradient due to its computational simplicity. Given an image \( f(x, y) \), the gradients at coordinates \( (x, y) \) in the x- and y-axis are given by \( g_x \) and \( g_y \), where:

\[
g_x = \frac{f(x+1, y) - f(x-1, y)}{2}
\]

\[
g_y = \frac{f(x, y+1) - f(x, y-1)}{2}
\]
**Figure 4** Detection of reflection regions of the battery charger at different viewing angles

Notes: (a1)-(c1) Battery charger images at viewing angles 80°, 98° and 121°, respectively; (a2)-(c2) respective estimated reflection images; (a3)-(c3) respective detected reflection regions in the segmented images with control constant $K = 1$

**Figure 5** Detecting reflection on white-leather surfaces

Notes: (a1) Leather cover image without light reflection at viewing angle 90°; (b1) leather cover image with light reflection at viewing angle 85°; (a2) and (b2) respective reflection images of (a1) and (b1); (a3) and (b3) respective detected reflection regions
that we do not use the sum, but the product, of markers used for registration.

The four square frames are the selected markers for registration. As shown in Figure 6, the image is divided into multiplicative gradients as the final fiducial markers for image registration. We retain only the two with the largest marker. Once four markers are chosen from individual subimages, we sum up the gradient magnitudes in the window in individual x- and y-axis, and obtain $G_x$ and $G_y$:

$$G_x(x, y) = \sum_{i, f} g_x(x + i, y + f)$$

$$G_y(x, y) = \sum_{i, f} g_y(x + i, y + f)$$

$$(x', y') = \arg \max \{ G_x(x, y) \cdot G_y(x, y) \}, \forall (x, y) \in \text{Subimage}$$

(10)

$(x', y')$ is the central coordinates of the selected marker. Note that we do not use the sum, but the product, of $G_x$ and $G_y$ to prevent the selection of a high-contrast straight line as the marker.

Once four markers are chosen from individual subimages, we retain only the two with the largest multiplicative gradients as the final fiducial markers for image registration. As shown in Figure 6, the image is divided into quadrants. The four square frames are the selected markers for individual subimages, and the two solid square frames that present most unique patterns in the object surface are the final markers used for registration.

Let $(x_{T,1}, y_{T,1})$ and $(x_{T,2}, y_{T,2})$ be the centers of the two selected marker windows in the template image and $(x_{S,1}, y_{S,1})$ and $(x_{S,2}, y_{S,2})$ the corresponding matched points in the test image based on the evaluation of the normalized cross-correlation (NCC) in a small search region. The translations in the x- and y-axis are then given by:

$$\Delta x = \frac{1}{2} (x_{S,1} + x_{S,2}) - \frac{1}{2} (x_{T,1} + x_{T,2})$$

$$\Delta y = \frac{1}{2} (y_{S,1} + y_{S,2}) - \frac{1}{2} (y_{T,1} + y_{T,2})$$

(11)

The rotational angle $\Delta \theta$ is obtained from:

$$\Delta \theta = \theta_S - \theta_T$$

(12)

where:

$$\theta_T = \tan^{-1} \left( \frac{y_{T,1} - y_{T,2}}{x_{T,1} - x_{T,2}} \right)$$

$$\theta_S = \tan^{-1} \left( \frac{y_{S,1} - y_{S,2}}{x_{S,1} - x_{S,2}} \right)$$

Figure 6 Automatic marker selection in the quadrants of an image.

4.2 Template matching

In order to detect the difference (i.e., a potential defect) between the template image and the registered scene image, a template-matching process is required to compare the similarity (or dissimilarity) pixel by pixel. The template-matching method should be robust to minor misalignment even in a registered image. In this study, we evaluate a fast sum of absolute differences (SAD) method, a widely used NCC measure, and a newly proposed optical-flow matching.

The SAD method is a simple algorithm for finding the similarity between two small image blocks. It takes the absolute difference between each pixel in the template block.
**Figure 7** Marker selection and image registration for a diecast model jeep

(a) Template image; (b1) test image with a 10-pixel translation; (c1) test image with a 3° rotation; (b2) and (b3) difference images between (a) and (b1) before and after registration, respectively; (c2) and (c3) difference image between (a) and (c1) before and after registration, respectively; (the white dotted squares show the selected markers and the matched instances)

**Figure 8** Marker selection and image registration for a mouse

(a) Template image; (b1) test image with a 10-pixel translation; (c1) test image with a 3° rotation; (b2) and (b3) difference images between (a) and (b1) before and after registration, respectively; (c2) and (c3) difference image between (a) and (c1) before and after registration, respectively; (the white dotted squares show the selected markers and the matched instances)
and the corresponding pixel in the test block. These differences in the block are then summed up and create a simple similarity measure. The SAD value at pixel coordinates \((x, y)\) is given by:

\[
SAD(x, y) = \sum_{j} \left| f_T(x + i, y + j) - f_S(x + i, y + j) \right|
\]

(14)

where \(f_T(x, y)\) and \(f_S(x, y)\) are the gray levels at \((x, y)\) in the template image and the registered scene image, respectively. Coordinates \((x + i, y + j)\) are the neighboring pixels of \((x, y)\). A perfect match of two correlation coefficients \(d\) and the corresponding pixel in the test block. These differences in the block are then summed up and create a simple similarity measure. The SAD value at pixel coordinates \((x, y)\) is given by:

\[
SAD(x, y) \approx \mu_{\text{SAD}} + C \cdot \sigma_{\text{SAD}}
\]

(15)

where \(\mu_{\text{SAD}}\) and \(\sigma_{\text{SAD}}\) are the mean and standard deviations of SAD values in the whole image.

For NCC, the correlation coefficient is used as the similarity measure for each pixel defined in a small neighborhood window. The correlation coefficient at pixel \((x, y)\) is defined as:

\[
\delta(x, y) = \frac{\sum_{i,j} \left[ f_T(x + i, y + j) - \bar{f}_T(x, y) \right] \left[ f_S(x + i, y + j) - \bar{f}_S(x, y) \right]}{\sum_{i,j} \left( f_T(x + i, y + j) - \bar{f}_T(x, y) \right)^2} \cdot \sum_{i,j} \left( f_S(x + i, y + j) - \bar{f}_S(x, y) \right)^2}
\]

(16)

where \(\bar{f}_T(x, y)\) and \(\bar{f}_S(x, y)\) are the mean gray levels of the neighborhood windows in the template image and the registered scene image, respectively. A perfect match of two identical image blocks will give a match score of 1. A pixel \((x, y)\) with correlation coefficient \(\delta(x, y)\) is classified as a defect point if:

\[
\delta(x, y) < \mu_\delta - C \cdot \sigma_\delta
\]

(17)

where \(\mu_\delta\) and \(\sigma_\delta\) are the mean and standard deviations of correlation coefficients \(\delta\) in the whole image.

The conventional matching methods of SAD and NCC measures are sensitive to object edges in the image. In this study, we also propose an optical-flow-based matching method for similarity measurement. It is tolerant of minor misalignment of object edges and yet responsive enough for small local defects. We use the Lucas-Kanade (1981) differential method for the computation of optical flow. The basis of differential optical flow is the motion constraint equation under the constant-brightness assumption:

\[
f(x, y, t) = f(x + dx, y + dy, t + dt)
\]

(18)

where \(f(x, y, t)\) is the gray value of pixel \((x, y)\) at frame \(t\) and is shifted by \(dx\) and \(dy\) in the respective \(x\)- and \(y\)-axis at image frame \(t + dt\). The second term in equation (18) can be approximated by the first-order Taylor expansion and, thus:

\[
\frac{\partial f}{\partial x} u + \frac{\partial f}{\partial y} v = -\frac{\partial f}{\partial t}
\]

where \(u = dx/dt\) and \(v = dy/dt\).

Assuming a constant shift in a small neighborhood window \(N_{xy}\) for pixel \((x, y)\), the optical-flow vector \([u, v]\) can be solved by the least square method in the following matrix form:

\[
V = A^+ \cdot b
\]

(19)

where \(A^+\) is the pseudo-inverse of \(A\), and:

\[
A = \begin{bmatrix} f_{x1}^1 & f_{x1}^2 & \cdots & f_{x1}^N \\ f_{y1}^1 & f_{y1}^2 & \cdots & f_{y1}^N \\ \vdots & \vdots & \ddots & \vdots \\ f_{xN}^1 & f_{xN}^2 & \cdots & f_{xN}^N \end{bmatrix}, \quad b = \begin{bmatrix} u^1 \\ v^1 \\ \vdots \\ u^N \\ v^N \\ \vdots \\ u^N \end{bmatrix}
\]

For defect detection applications, the discrete forms \(f_{xi}^ni\) and \(f_{yi}^ni\) of the derivatives \(\partial f/\partial x\) and \(\partial f/\partial y\) for pixel \((x_i, y_i)\), \(i = 1, 2, \ldots, N\), are defined in a small neighborhood window \(N_{xy}\) of the template image \(f_T(x, y)\) and the registered scene image \(f_S(x, y)\) are given by:

\[
f_{xi}^ni = \frac{1}{2} \left[ f_T(x_i + 1, y_i) - f_T(x_i - 1, y_i) \right]
\]

\[
f_{yi}^ni = \frac{1}{2} \left[ f_T(x_i, y_i + 1) - f_T(x_i, y_i - 1) \right]
\]

(20)

\[
\frac{f_T(x_i, y_i)}{C_2} = \frac{f_S(x_i, y_i)}{C_2}
\]

(21)

The optical-flow magnitude at pixel \((x, y)\) is defined as:

\[
L(x, y) = \sqrt{u^2(x, y) + v^2(x, y)}
\]

(22)

The optical-flow magnitude is then used as the similarity measure. A defective region yields large flow magnitudes, whereas a defect-free region results in very small flow magnitudes. A pixel \((x, y)\) is classified as a defect point if:

\[
L(x, y) > \mu_L + C \cdot \sigma_L
\]

(23)

where \(\mu_L\) and \(\sigma_L\) are the mean and standard deviations of flow magnitude \(L\) in the whole image. Since the optical-flow process can estimate the shift of a pixel in the scene image with respect to the template image, it is well tolerant of the minor displacement between the two compared images.

5. Experimental results

The system configuration and specifications of the robot vision system have been described in Section 2. The proposed detection algorithms were coded in the C+ language and implemented on a Pentium Core2 Duo, 2.67 GHz personal computer. The image used in this study is very large in size. The computation time of a 1,600 × 1,200 image is 3.55 s for reflection detection. Note that this processing time is required only in the planning stage, and not in the inspection stage.

5.1 Effects of changes in parameter values of \(K\) and \(C\)

In the proposed algorithms for surface defect inspection of 3D objects, there are two main parameters that affect the detection results. One is the control constant \(K\) for reflection detection, and the other is the control constant \(C\) for defect
detection. The effects of changes in parameter values of \( K \) and \( C \) are separately evaluated in this subsection.

Generally, too small the \( K \) value may generate random noise, while too large the \( K \) value may reduce the reflection area detected in the image. Figure 9(a1) and (b1) shows the test samples of a battery charger and a diecast model jeep to evaluate the effect of changes in the value of control constant \( K \) for reflection segmentation. Figure 9(a2)-(a6) and (b2)-(b6) shows, respectively, the detected reflection regions of images (a1) and (b1) with varying control constant \( K \) from 0.5 to 3.0. The detection results show that the detected reflection regions are reduced when the parameter value of \( K \) increases. A very small value of \( K = 0.5 \) generates a few noisy points in the object edges. The experimental results indicate the reflection region can be reliably detected with \( K \) value in the range between 1 and 2, and the proposed reflection-detection method is not sensitive to a small change of \( K \) value.

The control constant \( C \) is used to set up the threshold to segment the defect region in the image. Too small the \( C \) value gives a tight control and may generate noisy points. Too large the control constant \( C \), however, gives a loose control and may cause the reduction of defect size. For practical implementation, the control constant \( C \) can be learned from a set of defect-free sample images by setting the parameter to the minimum value that results in no false alarms for all the test samples. Figure 10 shows an electrical adapter used to evaluate the effect of changes in the value of control constant \( C \), where image (a) is the template image, and images (b1) and (c1) are defect-free and defective test samples at the same viewing angle. Figure 10(b2)-(b6) and (c2)-(c6) is, respectively, the detection results of defect-free sample (b1) and defective sample (c1) with parameter \( C \) varying from 0.5 to 3.0. The detection results show that a very small value of \( C = 0.5 \) generates noisy points for the defect-free image, as shown in Figure 10(b2). The detected defect size is gradually reduced as the parameter value of \( C \) increases. Because the defect size is generally very small with respect to the whole object size in the image, the control constant \( C \) can be set in the range between 1 and 2. The experimental results in Figure 10 also show that a \( C \) value in the range between 1 and 2 can produce good detection results.

5.2 Reflection detection

In the experiments on reflection detection, the same Gaussian filter of size \( 11 \times 11 \) with scale parameter \( \sigma = \sqrt{2} \) was applied to all test samples. Figure 11(a1)-(c1) shows the robot posing for a right-side view (inclined angle \( 45^\circ \)), a straight top view, and a left-side view (inclined angle \( 135^\circ \)) of the diecast model jeep. Figure 11(a2)-(c2) shows the sensed images showing the rear, top, and front of the miniature jeep composed of multiple planar and curved surfaces. Figure 11(a3)-(c3) shows the detected reflection regions of the respective images when the control constant \( K \) for reflection threshold is set at 2. It can be observed from the resulting binary images that all reflection areas on the jeep surfaces are accurately detected and segmented.

Figure 12(a1)-(e1) shows the sensed images of a cellular phone with viewing angles declining from \( 90^\circ \) to \( 82^\circ \). The display window of the cellular phone is highly reflective in the straight top-view image. The reflection is then gradually reduced as the viewing angle is changed from \( 90^\circ \) to \( 82^\circ \). Figure 12(a2)-(e2) shows the corresponding detection results.
Figure 10 Effect of changes in the control constant $C$ for defect segmentation

Notes: (a) Template image of an electrical adapter; (b1) defect-free test image; (c1) defective test image with a bold scratch; (b2)-(b6) detection results of defect-free image (b1) with varying $C$ values; (c2)-(c6) detection results of defective image (c1) with varying $C$ values
of the reflection regions as binary images. All the reflection regions are reliably detected with a control constant $K = 1$.

Figure 13(a1)-(d1) further shows the sensed images of a white plastic mouse at viewing angles of 80°, 88°, 95° and 100° (in a horizontal scanning direction of the image). The convex surface of the mouse presents a circular spark over a wide range of viewing angles. The detection results in Figure 13(a2)-(d2) shows that the proposed method can also detect well the reflection on a curved surface. The detected reflection regions are superimposed on the original gray-level images, so that the location changes of the reflection regions at different viewing angles can be easily observed. As seen in Figure 13(a3)-(d3), the detected reflection regions are significantly shifted from the left to the right in the image when the viewing angle is changed from 80° to 100°. The printed characters cannot be observed at viewing angle 88° (in image (b1)) when they are concealed by the reflection. They can be present completely at viewing angle 100° (in image (b1)).

In our implementation, the hand-held devices generally are only composed of six surfaces and, thus, a large angular step of 22.5° is applied along a scan trajectory. It initially takes only seven viewing angles from 22.5° up to 157.5° with an increment of 22.5°. For each of the seven angles, the end-effector-mounted camera then moves with $\pm 1°$ increment around the given angle and finds the image without reflection regions. For the object surfaces that no reflections can be removed in any viewing angles, the images with different reflection locations on the surface are retained as the templates, and the reflection region in each template image is marked as a “don’t-care-region” which will be ignored in the inspection process. This ensures all the required inspection areas are complete.

5.3 Template matching for defect detection
The performance of the proposed optical-flow similarity measure for defect detection is compared with NCC and SAD. Prior to the template-matching process, the whole inspection procedure from reflection detection, marker selection to image registration described previously is applied to all test samples discussed in this subsection.

Figure 14 shows the defect detection results of the battery charger. The template image of the charger at the viewing angle of 57° is shown in Figure 14(a). Figure 14(b1) is a defect-free test sample, and Figure 14(c1) is a defective sample with a thin scratch on the surface. The value of the control constant $C$ for the threshold of similarity measure is determined such that the defect-free test sample generates the least noise and the defect is well presented in the segmented image for individual comparative methods. The binary images in Figure 14(b2)-(b4) are detection results of the defect-free test sample from the NCC method with $C = 2$, the SAD method with $C = 3$, and the optical-flow measure with $C = 1$, respectively. The binary images in Figure 14(c2)-(c4) are the detected defect of the defective test sample from the three comparative methods. The detection results show that the optical-flow matching method can detect the thin scratch well, without presenting noise. The SAD method presents false defect points around the edges of printed characters.
The NCC method is also sensitive to object edges, and is computationally expensive with a large neighborhood window size.

Figure 15 shows the defect detection results of the cellular phone at the viewing angle of 79°. Figure 15(a) is the template image. Figure 15(b1) and (c1) shows a defect-free and a defective test sample, respectively. The resulting binary images in Figure 15(b2)-(b4) and (c2)-(c4) were obtained from NCC, SAD and optical-flow matching. Again, the optical-flow measure can reliably detect the small defect without showing any noise. The SAD method can also identify the defect with noisy points on the two vertical edges of the phone.

Figure 16 further shows the defect detection results of the electrical adapter at the viewing angle of 90°. Figure 16(a) is the template image. Figure 16(b1) is a defect-free sample, and Figure 16(c1) is a defective sample with a bold scratch. The detection results in Figure 16(b2)-(b4) and (c2)-(c4) from the three comparative methods also reveal that the optical-flow matching method can accurately detect the scratch defect.
Figure 13 Detecting reflection on a mouse with curved surfaces

Notes: (a1)-(d1) Sensed images at viewing angles of 80°, 88°, 95° and 100°; (a2)-(d2) detected reflection regions with control constant $K = 1$; (a3)-(d3) superimposing the detected reflection region on the original image.
Figure 14 Defect detection of the battery charger from different matching methods

Notes: (a) Template image at viewing angle 57°; (b1) defect-free test image at the same viewing angle; (c1) defect test image with a scratch on the surface; (b2)-(b4) detection results of the defect-free sample (b1) from NCC, SAD and optical flow measures, respectively; (c2)-(c4) detection results of the defective sample (c1) from the three comparative methods
**Figure 15** Defect detection of the cellular phone

Notes: (a) Template image at viewing angle 79°; (b1) defect-free test image; (c1) defect test image; (b2)-(b4) detection results of the defect-free sample (b1) from NCC, SAD and optical flow measures, respectively; (c2)-(c4) detection results of the defective sample (c1) from the three comparative methods.
Figure 16 Defect detection of the electrical adapter

Notes: (a1) Template image at viewing angle 90°; (b1) defect-free test sample; (c1) defect image with a bold scratch; (b2)-(b4) detection results of the defect-free sample (b1) from NCC, SAD and optical flow measures, respectively; (c2)-(c4) detection results of the defective sample (c1) from the three comparative methods.
The NCC method shows only scattered points of the defect. The SAD method produces noisy edge points of the object in the defect-free image.

In the inspection stage, the processing time of image registration is 0.2 s. Given the large image of size 1,600 × 1,200 pixels, the required computation times of template matching are 0.39 s for SAD, 36.38 s for NCC, and 1.98 s for optical flow. The SAD method is computationally very fast and very easy to implement. It should be used when the compared images can be precisely registered. The optical-flow matching method gives a moderate computation time. It should be used when the object may present minor displacement.

6. Conclusions

In this paper, we have presented a robot vision system for surface defect detection of 3D objects. For the qualitative inspection of 3D object surfaces, the viewing angles of the end-effector-mounted camera must cause no or minimum reflection on the object surfaces so that the reflection region will not be detected as a defect and an actual defect will not be concealed. We have used an illumination-reflection model to detect and segment the reflection region in a sensed image. The robot vision system can thus automatically avoid the high-reflection viewing angles and find the reflection-free camera angles for surface inspection.

To eliminate variation from robot repeatability and object displacement, we have also proposed an automatic marker-selection process to determine two discriminative fiducial markers for each template image at a specific viewing angle. The selected markers contain maximum gradient information and thus give the most complicated edge patterns for reliable image registration. Experimental results have shown that the optical-flow matching method with the proposed image-registration process performs best for detecting small local defects on 3D object surfaces. The proposed robot vision system is feasible for surface defect inspection of 3D objects.

In this study, we used simple scan trajectories based on the two orthogonal principal components of the object in the straight top-view image to observe all surfaces of the 3D object. A more efficient method of view planning that finds the minimum required number of viewing angles under the reflection-free constraints is currently under investigation.

References


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