Automated Vision-Based System for Inspecting Glue Route Quality in Harddisk Drive Top Cover Assembly

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Abstract

An automated vision-based system for inspecting glue route quality in harddisk drive top cover assembly is proposed. It consists of three units: user interface, processing and material handling. In the image processing unit, the image is aligned and then the glue route is extracted. Four partial dark-field images were obtained from each plate. For each image, the reference coordinate system is first determined to construct a rigid-body transformation from predefined template images. Two binary templates were used to identify the defective route in the test image. Our system is efficient and can achieve a very high accuracy.

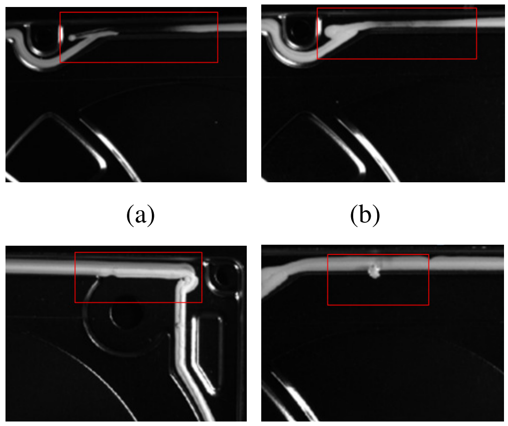
1. Introduction

Rubber seal attached to the harddisk-drive top cover is an important part to ensure no contamination enters into the internal parts. This seal is attached on a glue route made by a glue dispenser. Examples of these can be seen in Figure 1.

(a) (b)

Figure 1: Example of harddisk-drive top cover (a) with rubber seal (b) with glue route

In the harddisk assembly process, too thin or incomplete glue trace along its route may cause loose seal attachment while too thick, protruding or dislocated trace could generate contamination within the internal compartment of the drive after a curing process. This can cause instability or failure to the drive. Examples of defects are shown in Figure 2.



(a) (b) (c) (d)

Figure 2: Glue route defects (a) incomplete (b) too thin (c) offset and too thick (d) protruding

The current inspection process is based on human operators. Its accuracy and efficiency is dependent of experience of the inspector. Moreover, contamination may occur due to improper handling of the workpiece. Therefore, we propose an automated visual inspection system for solving this problem.

This paper is organized as follows. Previous work is described in the next section. Section 2 presents overview of our machine. Our main machine vision part is explained in Section 3. In Section 4, we present some experimental results. Finally, conclusions are drawn in Section 5.

1.1. Previous work

Yung Ting et al. [1] designed a visual inspection system to inspect glue route. They use back-propagation neural network (BPNN) to identify defects including deformation, offset, contamination and open. Although, they reported good performance, this system required a great deal of training data.

Similar to glue route inspection, inspecting copper print on printed circuit boards is also investigated. Moganti et al. [3] summarized PCB inspection algorithms. Rambabu K et al. [2] design an automated visual inspection system to find defect on fine patterns of printed circuit board. They divide the defects into three groups: (1) Dust particles, Open & Shot, (2) Mouse bite and (3) Protrusion & Islands / Pin-holes. They employ three techniques called Referential, Non-Referential and Hybrid inspections to find defects. They reported that referential inspection did not find all defects due to instability of their position and size; however, the hybrid approach performed best due to combined advantages of referential and non-referential approaches.

2. System overview

Our proposed automated visual inspection system is illuminated in Figure 3. It consists of three units: material handling, user interface and processing modules.

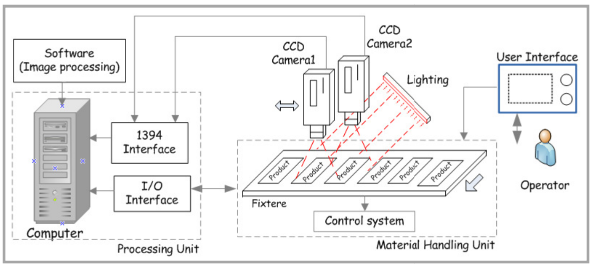
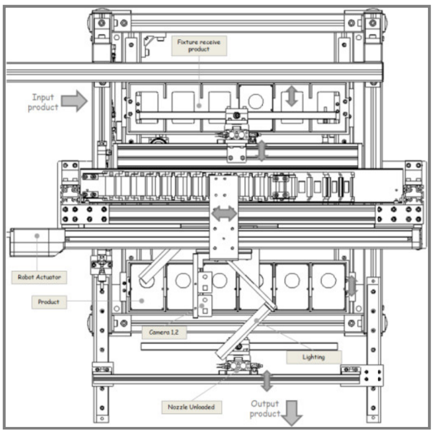
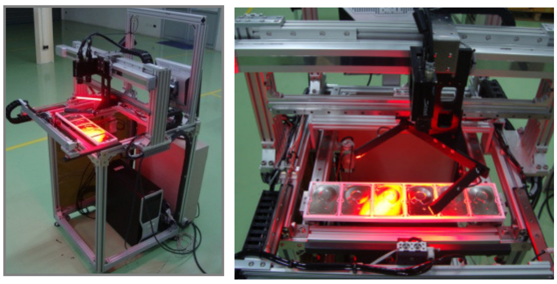


Figure 3: System overview

The material handling unit performs loading, unloading and handling parts for inspection. It starts from simultaneously unloading 6 parts from the glue dispenser by vacuum nozzles then places them to an alignment fixture. Finally the fixture is moved to the inspection station. Two cameras and a lighting module is used for image acquisition. The load/unload operation is performed by pneumatic actuators while the image capturing is attached to a linear robot actuator. Our inspection machine is shown in Figure 4.



(a)



(b) (c)

Figure 4: Our inspection machine (a) Top view of mechanical parts and machine mechanism (b) the inspection machine (c) lighting setup

The user interface unit is a touch screen panel for interacting between user and the machine. The user can control machine operation, set system parameters, and monitor inspection results as well as status of the machine.

The processing unit accounts for image acquisition and image processing. When products were moved to position of image capturing, the material handling controller signals the acquisition to start capturing images. Two Basler scA1000-fm monochrome cameras were used to achieve a cost-effective designed (0.5 mm) resolution. This allows an alignment error of less than 0.2 degree. Two captures are required for each plate. The lighting is installed to achieve a (partial) dark-field imaging [4] to suppress reflections from the metal surface of the plate. Figure 4(c) shows our lighting setup. Each camera has a field of view (FOV) illustrated in Figure 5; therefore, each plate has four partial images. Example of a set of the partial images is shown in Figure 6.

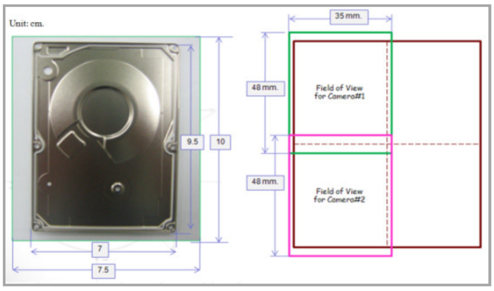


Figure 5: Field of view of each camera

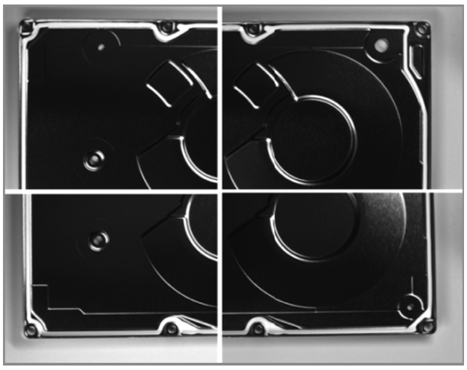


Figure 6: Sample partial images of the same plate

3. Machine vision methods

For each partial image, the inspection algorithm can be divided into 3 parts: reference coordinate determination, glue route segmentation and defect classification. Figure 7 shows block diagram of the algorithm.

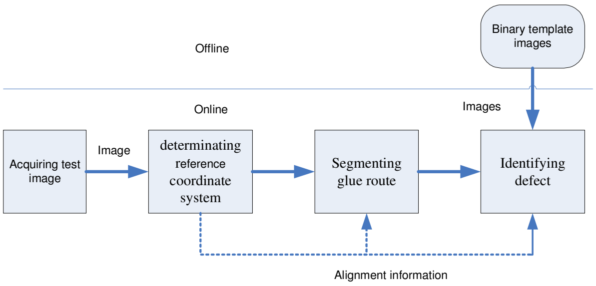


Figure 7: Block diagram of vision algorithms

1.2. Reference coordinate system determination

Although guide pins were used to align the plate in the fixture, small misalignment can occur due to mechanical tolerances. This process is to accurately refine the reference coordinate system for the rigid-body transformation. Vertical and horizontal rakes are used to detect edges of the top cover. Subpixel edge detection technique [5] was employed in each line within the rakes. This is done by finding the maximum of gradient magnitude along the line then a parabola is fitted around the maximum. The close-form solution is found as

$$\hat{x} = \frac{-1}{2}\frac{(I_m - I_{m+1})x_{m-1}^2 + (I_{m+1} - I_{m-1})x_m^2 + (I_{m-1} - I_m)x_{m+1}^2}{(I_m - I_{m+1})x_{m-1} + (I_{m+1} - I_{m-1})x_m + (I_{m-1} - I_m)x_{m+1}} \quad (1)$$

where x_m and I_m are the (pixel-precise) position and the magnitude of the maximum of gradient, respectively. The other points are the previous and next pixel around the maximum.

The edge points detected from each rake are fitted to a line using least squares [4]. Hessian normal representation of the line, eq. (2), is used to minimize the geometric error. A close-form solution [5] is also available.

$$\alpha x + \beta y + \gamma = 0 \quad (2)$$

In the reference coordinate system, the principal axis and the origin is defined by the vertical line and the intersection point of the two lines, respectively. Figure 8 shows an example of the reference coordinate system.

Figure 8: Example of reference coordinate system determination

1.3. Glue route segmentation

Although the dark field lighting can suppress most reflections from the metal surface, strayed reflections from some surface patterns remain in the image as shown in Figure 8. Therefore, thresholding was used to roughly segment bright regions from the background of image. The glue route is extracted by selecting a blob covering a transformed location from a predefined reference position. An example of this result is shown in Figure 9.

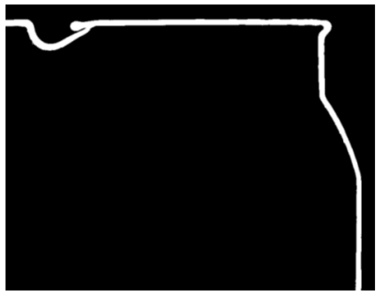
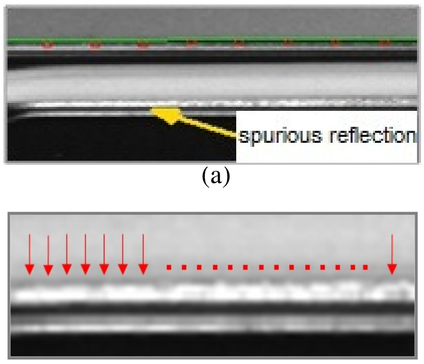


Figure 9: Example of roughly segmenting and selecting glue route

Spurious reflections (Figure 10(a)) of metal plate near glue route make it difficult to separate between the glue route and the metal plate. We eliminate this residual reflections by scanning from the center of the (selected blob) route across its local direction to look for sharp rising in intensity level to identify the residual and (if any) to eliminate it. Figure 10(b) illustrates the process.



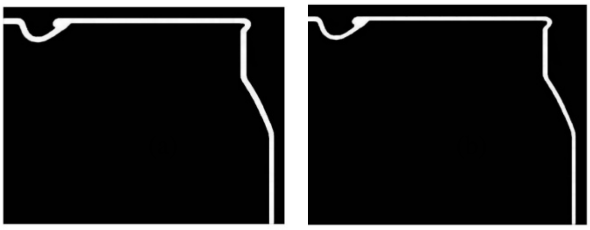
(a)

(b)

Figure 10: Spurious reflections (a) residual reflections from metal plate (b) residual reflection suppression

1.4. Defect identification

The idea of our method is to identify if the glue route is formed within a tolerance, in our case, i.e., within 0.9 mm. to 1.3 mm. This can be formed using two binary templates: inner and outer bound templates (obtained from erosions and dilations of golden model). If the transformed route of the test specimen covers the inner template completely and lies absolutely within the outer template, the route is acceptable. A top plate with perfect glue route is used to generate the templates in our work. Figure 11 shows a set of the two templates of the top-right FOV.



(a) (b)

Figure 11: Inner and outer bound templates (a) outer bound (b) inner bound

Condition 1: the transformed route of the test specimen must cover the inner template completely.

$$T1 \text{ AND } I = T1 \tag{3}$$

Condition 1: the transformed route of the test specimen must cover the inner template completely.

$$T2 \text{ AND } I = I \tag{4}$$

where the inner and the outer bound templates are represented by *T1* and *T2*, respectively. *I* is the binary glue route image obtained from the preceding method.

To accept a top-cover plate, all four partial images must satisfy both conditions. If a partial image from the set cannot meet the first condition, the plate is labeled as NG without further processing.

4. Experiments

We tested our system on 120 test specimens. The specimens were loaded automatically from the glue dispenser. Although, only GO/NG results were required, we identified each defective type for detailed analysis. The defect type of these glue routes could be incomplete, too thin, offset, too thick and protruding. We randomly loaded the samples (in sets of 6 pieces) into the machine and obtained the result as shown in Table 1.

Table 1 Experimental result

	Defect type					No defect
	Incom-plete	Too thin	Offset	Too thick	Protrud-ing	
Total	5	5	5	5	5	95
GO	0	0	0	0	0	93
NG	5	5	5	5	5	2

From Table 1, the machine achieved 98.3%. The errors found were over-reject cases. Two good specimens were classified as defect due to their offsets and residual reflections around their margins.

5. Conclusion

An automated machine for inspection glue route is proposed. It can automatically load HDD top cover plates from a glue dispenser machine in set of six. The image acquisition module consists of two cameras and lighting system. Four partial dark-field images were obtained per plate. For each image, the reference coordinate system is determined to construct a rigid-body transformation from template images. Two template images were built to specify tolerance of the glue route. The transformed route of the test specimen is compared to the templates and defective plates can be identified. The system was tested on 120 sample plates and we achieved a very accurate result. Improvements will be focused on more effective ways to eliminate spurious reflections around the glue route.

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