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Image based contamination detection on hard disk head gimbal assembly

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***Abstract*— Contamination may appear in various stages of hard disk manufacturing including the head gimbal assembly. Currently, the detection of contamination requires manual intervention. An image based automatic contamination detection strategy is therefore presented. After a preprocessing step, the contamination detection algorithm first detects potential areas of contamination using circle detection. Then, each of the contamination contenders are classified as either a contamination or non-contamination using a set of specific rules. The algorithm has been tested on 1,050 head gimbal assembly images of which 313 depicted contaminations. Our preliminary results yields an accuracy of 73.8% with a false negative rate of 34.8% and a false positive rate of 23.6%. Future work includes fine-tuning the contamination classification rules.**

Keywords-component; Head gimbal assembly; hard disk manufacturing; circle detection.

I. INTRODUCTION

The demand for storage is constantly growing. Advancement in multimedia technologies leads to high definition multimedia content that result in increasing storage needs. Moreover, more people are relying on modern multimedia technology than ever before. Although users are increasingly storing their information in the cloud, the cloud services still relies on physical storage. Big Data is one of the new storage hungry emerging areas of computer science.

To meet the increasing storage demands hard disk manufacturers need to constantly improve their technology and manufacturing processes. Challenges during manufacture include defects introduced during soldering and contamination.

This study addresses one particular challenge during hard disk manufacture, namely that of contamination that is introduced during head gimbal assembly. In the manufacturing plant discussed herein, still images are captured by a set of cameras as the automatically assembled units are transported via conveyer belts. These images are then automatically inspected using the commercial COGNEX image analysis software and anomalous units are selected for manual inspection. One problem with COGNEX is its lack of accuracy and it therefore is set up with a very high false negative rates.

Consequently, a large number of units needs to be manually inspected using microscopes with typically 40× magnification. This manual inspection process is time-consuming, error-prone and expensive. Moreover, specially trained and experienced personnel is needed. To overcome the problems associated with manual intervention in harddisk manufacturing processes this study set out to explore a new automatic contamination detection method.

II. BACKGROUND

Two major issues in electronics manufacturing is the detection of manufacturing defects and contamination. Defect detection has received quite some attention. Various defect detection approaches has been proposed for the inspection of semiconductor wafers [1, 2], LED dies [3] solar wafer surfaces and hard disk drive media [4, 5]. Among these, the detection of defect soldering joints is a major issue [6].

Another problem that has received attention is the detection of scratches, dings, glove marks and contamination on hard disk media surfaces [7]. For this purpose the mean shift clustering approach has proved useful.

Unlike contamination detection, the literature on noise reduction is vast [8, 9, 10]. Approaches include the use of morphological operators [8], Baysian methods [9] and various filtering approaches [10]. The purpose is thus to eliminate noise. The contamination detection problem, however, can be considered the inverse of the noise detection problem, where the objective is to enhance the presence of noise in the image such that its presence can be detected with a high confidence. The literature on contamination detection is comparatively more limited. One exception is automatic air and gas pollution detection, which is a very active area of research. However, we have not found the methods employed in this field to be directly applicable to the hard disk contamination detection problems.

Contamination detection has much in common with the problem of counting objects in images [11, 12]. Object counting approaches typically employ Hough transforms [11, 12] or machine learning [12]. Applications of object counting include head counting, that is, counting and tracking people [13] and automatically counting bacteria [14]. The problem of counting bacteria on Petrie dishes is somewhat simpler as the background is uniform. The head gimbal assembly, however, has a defined structure. One potential problem with basic object counting methods is that a contamination may occur on the lines of this structure. A successful contamination detection method needs to both be able to detect contaminations that appear on parts of the image with even backgrounds and contaminations that appear on the structures represented by the edges in the image.

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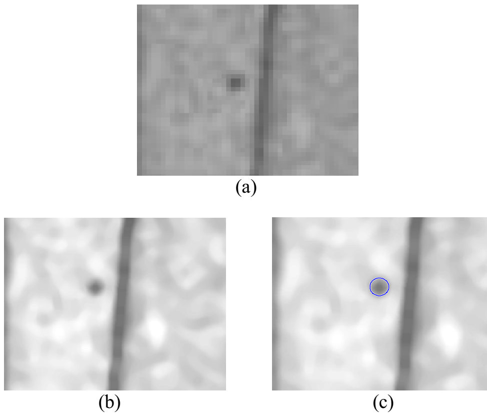


Figure 1. Detected circle in up-sampled image; a) original image, b) up-sampled and median filtered image, and c) detected circle.

Another approach to both fault detection and contamination detection is to compare images with fault-free template images [15]. The problem with this approach is that a high accuracy image registration approach is needed, which may be more difficult to conduct accurately with medium or low resolution images. Moreover, manufacturers also occasionally change their designs and the template images therefore need to be changed. It is thus desirable with a method that does not rely on template image comparisons.

III. METHOD

The method has three main steps. First, the input image is preprocessed. Next, potential contamination areas are identified using circle detection. Finally, each of the contamination contenders are classified as being either a contamination or not. The details of the approach are outlined in the following sections.

A. Preprocessing

The input images used for contamination analysis in this study is based on 2400×2000 pixel (96 dpi) RGB images with top-views of the HGA. Normalized cross correlation [16] is employed to determine the region of interest in relation to an ABS template image. A sub-image representing the 490×414 pixel region of interest is extracted and subsequently converted to gray scale. Fixed image parameters are used since it is assumed that the camera capturing the HGA top view images is stationary in relation to the units on the conveyer belt.

B. Contamination contenders

Circle detection is used to determine potential contamination areas in ABS gray scale images. As some contaminations are small, the grayscale ABS images are up-sampled [17] to achieve a factor five enlargement of the original ABS image. Up-sampled images are anti-aliased using a 15×15 median filter [18]. (In our experiment, the 15×15 median filter provided the best result as compared to other median filters of size 3×3 to 13×13) The anti-aliased images are subject to the circular Hough transform [19]. The result of the Hough transform is a list of potential contamination areas represented by circle centers and radii. These parameters are transformed back to the coordinate system of the original image.

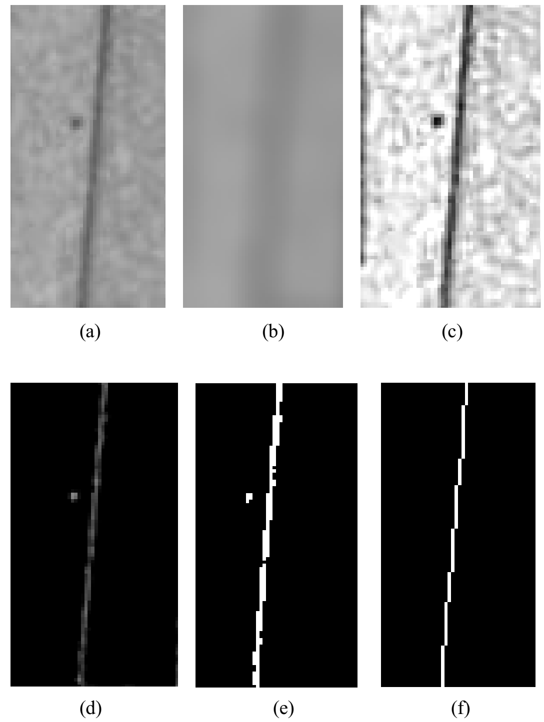


Figure 2. Detected circle and skeleton image; a) gray scale image, b) low-pass, c) heigh-pass, d) difference image, e) binary image and skeleton, and f) detected circle.

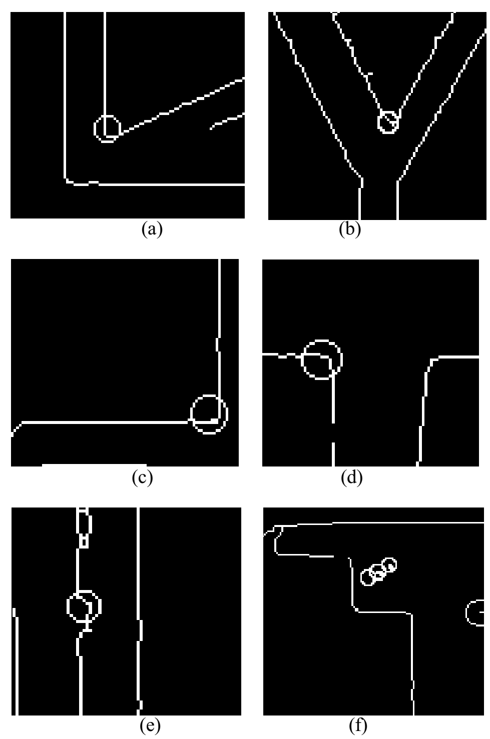


Figure 3. Detected circle, a)-d) non-contamination circle in corners, and e)-f) contamination circles

C. Contamination tests

To assess each of the circles marking contamination contenders the image skeleton is used. The original region of interest is low-pass filtered and high pass filtered. The difference between the low pass-filtered image and high pass-filtered image is then binarized using Otsu's method [20]. This method employs adaptive thresholding for image segmentation, where the local threshold computed from the variance within class. The morphological skeleton operator is subsequently applied to the binarized image to obtain a skeleton of the ABS binary image.

The area enclosed by each circle is classified as a contamination or non-contamination. The circles detected in the previous step are traced on the skeleton image with a 50% larger radii ($radius_{new} = (6/4) \cdot radius_{old}$) to find points where the circles crosses the skeleton.

Example cross points between the intersection of circumference and the skeleton of ABS are show in Fig. 5. If there are one cross point or less the circle might identify a contamination. Next, to determine if it is a contamination the white pixel in the binary image are counted. If the number of white pixel within the circle is greater than 45% the area it is marked as a contamination.

If there are two or more cross points the angle between two cross point relative to the circle center is calculated.

$$angle = cos^{-1}\left(\frac{AC \cdot BC}{|AC||BC|}\right) \tag{1}$$

where A and B are the two cross points and C is the circle center. The line between the points A and C is denoted AC, and the line between the points B and C are denoted BC. If there is more than one angle, the largest angle chosen. If the angle is greater than a threshold (100 degrees) the circle area is not considered a contamination.

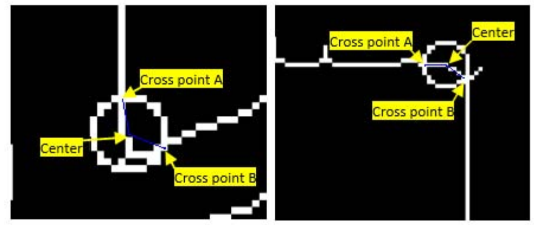
For circles with angles less than the threshold, the white pixels with intensity higher than 80% of maximum intensity from the gray scale image within detected circle are counted. If the white pixels constitute more than 45%, the area is considered contaminated.

IV. Experimental Evaluation

The proposed method was tested with 1,363 HGA images. This test suite comprised 1,050 images without contaminations and 313 images with contaminations. The method was implemented in Matlab and run on a Windows PC.

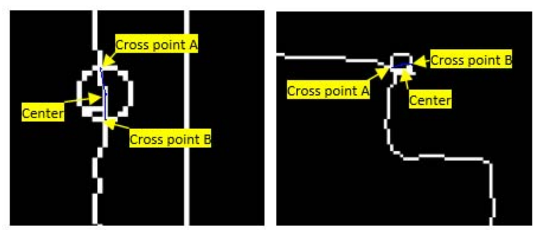
The preliminary experiments gave 84images incorrectly classified as not contaminated, giving a false negative rate of 26.8%. Moreover, 187 uncontaminated HGAs were incorrectly classified as being contaminated giving a false positive rate of 17.8%. The achieved accuracy was 74.19%.

Investigating the incorrectly classified cases in more detail it shows that some small contaminations with a low intensity on a uniform background goes undetected. This suggest that the algorithm needs to be tuned to be more sensitive to such contaminations appearing as small weak spots. At the same time such adjustments must be done without increasing the false positive rates as it is a chance that more non-contaminations will pass as contamination.



Non-contamination circle, angle = 123 Non-contamination circle, angle = 143

Contamination on Edge, angle = 68 Contamination circle, angle= 76



Contamination on Edge, angle = 168 Contamination circle, angle= 161

Figure 4. Angle between two cross points and center of circle.

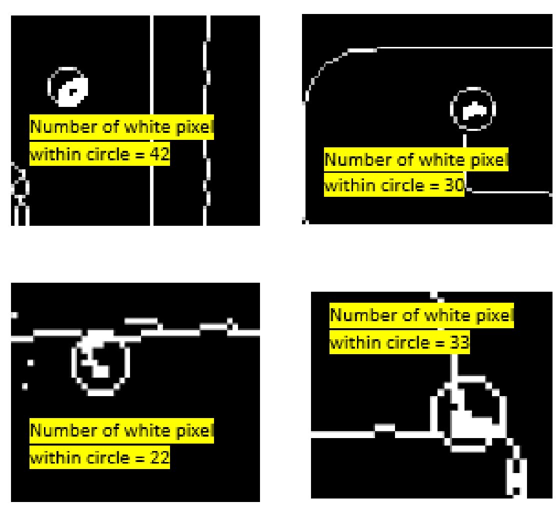


Figure 5. Counting the number of white pixel within a detected circle

Another challenge is the assessment of corners where the edges on the HGAs meet, that is, where the angle test is performed. Some corners are incorrectly classified as containing contamination when they in fact are uncontaminated.

All in all the problematic areas are the detection of small weak contaminations on even backgrounds and the corners where edges meet. These two areas are thus the ones that require attention in future work in order to improve the performance.

The method has acceptable performance in terms of computational effort. This is partially due to the efficient implementation of common image processing operators in Matlab and partially that the images that are subject to the processing are relatively small.

V. LIMITATIONS OF THIS STUDY

The study is addressing contamination found one type of harddisk technology under a specific set of manufacturing conditions. However, it is expected that the contamination detection method will generalize to other contamination detection problems. Another issue with the current tests is that these are based on low resolution images provided by the manufacturer using lossy jpeg image compression. Better results are expected with higher resolution images stored in RAW format.

VI. CONCLUSIONS

A novel algorithm for detecting contaminations on hard disk head gimbal assembly was proposed. The algorithm was designed to detect contamination both in areas of approximately constant background and contamination nearby or on top of non-uniform parts of the head gimbal assembly images. The method first preprocesses the input images, and then determines potential circular areas of contamination using circle detection. Finally, each of the circular regions are tested against a set of rules to determine if the particular case constitute a contamination or not. The current results are promising, but yet not sufficiently high to be employed in a production line. Future work will therefore focus on improving the contamination classification rules. Successful detection of contamination during hard disk manufacture holds great potential for improving the productivity, efficiency while lowering production costs.

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