Automated Distortion Defect Inspection of Transparent Glass Using Computer Vision

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Abstract – If a car windshield with distortion flaws will make object deformation and motion blur from the driver's sight easily, the drivers can cause visual misjudgment and have safety concerns on the road. This study presents the design of an automated distortion defect inspection system for car glass. In this study, a standard pattern with vertical lines displayed on a testing glass is captured as a testing image. First, a testing image is transformed to Hough domain to obtain the coordinates of the correct axis positions of multiple vertical lines. Through the accumulator analysis to find the peak points of the vertical lines in Hough domain, an image with new vertical lines is reconstructed from the selected peak points by taking the inverse Hough transform. Secondly, the binary testing image subtracts the binary reconstructed image to obtain a binary difference image of distortion defects. Finally, the cumulated deviation ratios of distorted segments are calculated and the offset pixel ratio of distortion segments reveals the level of distortion in the image. Experimental results show that the proposed method effectively determines whether there are distortion flaws with the occurrence location, as well as distortion segment cumulative pixel ratio.

Keywords: Industrial inspection; transparent glass; distortion defects; computer vision system; Hough Transform.

1 Introduction

If a car windshield with optical distortion flaws will make object deformation and motion blur from the driver's sight easily, the drivers can cause visual misjudgment and have safety concerns on the road. Since the distortion defects do not have regular shapes and clear boundaries, it is not easy to measure the magnitudes of distortion defects on curved windshields. Furthermore, the curved glass with the property of higher reflection increase the difficulty of discrimination of the distortion defects on car windshields. Therefore, this research aims at exploring the automated visual inspection of transmitted distortion defects of the curved car windshields.

The defective car windshields with transmitted distortion defects providing shape-distorted scene information may lead car drivers making wrong decisions when driving. Figure 1 shows the defective car windshield images with transmitted distortion defects on parking lot scene. The object shapes transmitted in the defective image are significantly distorted.

Figure 1. The defective car windshield images with transmitted distortion defects.

Inspection difficulties of surface defects are existing in manufacturing process. Surface defects affect not only the appearance of industrial parts but also their functionality, efficiency and stability. The most common detection methods for surface defects are human visual inspections. Human inspection is vulnerable to wrong judgments owing to inspectors' subjectivity and eye fatigues. Figure 2 shows the current inspection tasks by human visual judgment and the testing images with transmission of standard patterns. Furthermore, difficulties also exist in precisely inspecting distortion defects by computer-aided machine vision systems because when product images are being captured, the region of a distortion defect could expand, shrink or even disappear due to uneven illumination of the environment, different view angles of the inspectors, shapes of transmitted patterns, and so on.

Figure 2. Current inspection tasks by human visual judgment and the testing images with transmission of standard patterns.
Current computer-aided vision system (off-line and sampling) uses a horizontal or/and vertical lines pattern transmitted on glass to acquire images and quantize distortion magnitude for screening. It is hard to precisely inspect the glass distortion flaws by current machine vision systems due to high transmission and reflection. The property of higher transmission and reflection on curved glass increases the difficulty of discrimination of the distortion defects on car glass. In this research, the testing samples with length 25.4 cm, width 20.4 cm, and thickness 0.2 cm, were randomly selected from manufacturing process of car glass. Figure 3 shows the dimension of the testing sample with high transmission and reflection. This study proposes a Hough transform based approach to inspect transmitted distortion defects on curved car glass.

![Figure 3. Dimension of the testing sample with high transmission and reflection.](image)

2 Automated defect inspections

Automated visual inspection of surface flaws has become a critical task for manufacturers who strive to improve product quality and production efficiency [1-3]. Li and Tsai [4] proposed a wavelet-based discriminant measure for defect inspection in multi-crystalline solar wafer images with inhomogeneous texture. The proposed method performs effectively for detecting fingerprint, contaminant, and sawmark defects in solar wafer surfaces. Chiou [5] presented an intelligent method for automatic selection of a proper image segmentation method upon detecting a particular flaw type in roll-to-roll web inspection. The results show a significant reduction in misclassification rate. Perng et al. [6] developed a fast and robust machine vision system for wire bonding inspection. A new lighting environment was devised which will highlight the slope of the bonding wire and suppress the background from being extracted.


Regarding the distortion correction techniques, Duan and Wu [11] proposed a method for distortion correction in the barrel distortion of wide-angle lens. The cubic B-spline interpolation function was adopted to interpolate the surface and the bi-linear interpolation was used to reconstruct the gray level of pixels. Zhang et al. [12] presented a distortion-correction technique that can automatically calculate correction parameters, without precise knowledge of horizontal and vertical orientation. Based on a least-squares estimation, the algorithm considers line fits in both field-of-view directions and global consistency that gives the optimal image center and expansion coefficients. Ngo and Asari [13] presented an architecture design for real-time correction of nonlinear distortion in wide-viewing angle camera images. The architecture is designed based on the method of back mapping the pixels in the corrected image space to the distorted image space and performing linear interpolation of four neighboring pixel intensities.

Smith and Smith [14] proposed a methodology for improving the accuracy of machine vision calibration through applying regression analysis and neural network modelling. The regression analysis was employed for assisting with the data collection for neural network training and the neural network was developed for modelling the error in measured location of image features. Lin and Hsieh [15] proposed a vision system with a trapezoidal mask for image acquisition and applies cumulative sum control schemes to inspect distortion defects on curved car mirrors.

3 Proposed method

3.1 Image pre-processing

The captured testing image will be pre-processed in several steps. Figure 4 shows the original testing image and enhanced image performed the equalization approach for increasing contrast in gray levels. From the analysis of two corresponding intensity histograms, the contrast of gray levels has been increased and the vertical lines looked clearer in the enhanced image. Figure 5 depicts the enhanced normal and defective images and their corresponding binary images that the Otsu method [16] applied to do segmentation. Most of the vertical lines are clearly segmented from background in the binary images by Otsu method. The results reveal that the slight distortion defects in transparent glass surface are correctly separated in the binary image, regardless of insignificant distortion differences.
Figure 4. A testing image and its enhanced image with corresponding intensity histograms.

Figure 5. The enhanced normal and defective images with corresponding binary images.

3.2 Reconstruction of baselines image through Hough transform

Hough transform is a feature extraction technique used in image analysis, computer vision, and image processing. This transform was invented by P.V.C. Hough in 1962 [17]. It is commonly applied to find imperfect instances of objects within a certain class of shapes by a voting procedure. The purpose of the Hough transform is to perform groupings of edge points into object candidates by performing an explicit voting procedure over a set of parameterized image objects [18-19].

3.2.1 Hough transform

The simplest case of Hough transform is detecting straight lines [20]. In general, the straight line equation:

\[ y = ax + b \]  \hspace{1cm} (1)
\[ b = -ax + y \]  \hspace{1cm} (2)

The equation can be represented as a point \((a, b)\) in the parameter space. However, vertical lines pose a problem. They would give rise to unbounded values of the slope parameter \(a\). Thus, for computational reasons, the Hesse polar form is proposed of using the parametric representation of a line:

\[ x \cos \theta + y \sin \theta = \rho \]  \hspace{1cm} (3)

The variable \(\rho\) is the distance from the origin to the line along a vector perpendicular to the line and \(\theta\) is the angle between the x-axis and this vector. Each point in the \((x, y)\) plane gives a sinusoid in the \((\rho, \theta)\) plane. M collinear points lying on the line (Equation (3)) will give M curves that intersect at \((\rho, \theta)\) in the parameter plane. The Hough transform generates a parameter space matrix whose rows and columns correspond to these \(\rho\) and \(\theta\) values, respectively.

The linear Hough transform algorithm uses a two-dimensional array, called an accumulator, to detect the existence of a line. The dimension of the accumulator equals the number of unknown parameters, i.e., two values in the pair \((\rho, \theta)\). The input to a Hough transform is normally a binary image that has been segmented. Figure 6 shows the two Hough parameter spaces of the normal and defective binary images shown in Figure 5, respectively. We cannot find any difference between the normal and defective images in Hough parameter spaces.

3.2.2 Accumulators in Hough domain

Each element of the matrix has a value equal to the sum of the points or pixels that are positioned on the line represented by quantized parameters \(H(\rho, \theta)\). So the element with the highest value indicates the straight line that is most represented in the input image. For each pixel at \((x, y)\) and its neighborhood, the Hough transform algorithm determines if there is enough evidence of a straight line at that pixel. If so, it will calculate the parameters \(H(\rho, \theta)\) of that line, and then look for the accumulator's bin that the parameters fall into, and increment the value of that bin. The local maxima of the accumulators will give the significant lines. Figure 7 shows the corresponding relationship between spatial binary image and Hough parameter space. It indicates that the standard pattern with 7 line segments is displayed on
the binary image of a testing sample and there are 7 corresponding intersection points of curves in the Hough parameter space. The 7 vertical line segments are the targets need to be detected and their positions are located between the coordinates \(H(362, 91)\) and \(H(617, 91)\) in the Hough parameter space.

By finding the bins with the highest values, typically by looking for local maxima in the accumulator space, the most likely lines can be extracted. The simplest way of finding these peaks is by applying some form of threshold. Since the lines returned do not contain any length information, it is often necessary to find which parts of the image match up with which lines. Moreover, due to imperfection errors in the edge detection step, there will usually be errors in the accumulator space, which may make it non-trivial to find the appropriate peaks, and thus the appropriate lines. Figure 8 indicates that there are 3 peaks in the accumulators of coordinates \(H(362, 91)\) to \(H(490, 91)\) and 4 peaks in the accumulators of coordinates \(H(491, 91)\) to \(H(617, 91)\) in Hough parameter space. These 7 peaks represent 7 vertical line segments in the spatial domain.

![Figure 7](image1.png)

**Figure 7.** The corresponding relationship between spatial binary image and Hough parameter space.

![Figure 8](image2.png)

**Figure 8.** The 7 peaks and accumulators of coordinates \(H(362, 91)\) to \(H(490, 91)\) and coordinates \(H(491, 91)\) to \(H(617, 91)\) in Hough parameter space.

The Hough Transform generates parameter values \(\rho\) and \(\theta\) for all lines that could go through each detected (by a threshold, in this example) image point. Each possible line through each point then votes for its \(\rho\) and \(\theta\) values in a parameter space of possible \(\rho\) and \(\theta\) values. We limit and quantize this parameter space to get an accumulator space which accumulates votes for \(\rho\) and \(\theta\) values. After all possible lines through all detected points have voted, the accumulator space is searched for peaks that indicate which pairs of \(\rho\) and \(\theta\) parameters got the most votes. A peak indicates the presence of line and gives its parameters and equation in the image. We let the \(p_i\) be the location of peak \(i\) in the parameter space, \(k\) is the distance between two line segments, \(x_0\) is the initial location of the first line segment. The location of peak \(i\) can be determined as follows,

\[
p_i = \max(H(x_0 +((i-1)k), 91) \sim H(x_0 +(i \times k), 91))
\] (4)

After the positions of all peaks are located in parameter space, we need to transform them back to spatial domain for obtaining a baselines image. We assume \(q_i\) be the coordinate of the peak \(i\) in spatial domain. It can be obtained as follows,

\[
q_i = p_i - 360
\] (5)

The peaks in parameter space transformed back to spatial domain are the baselines in the reconstructed image. Figure 9 shows the testing binary image and corresponding reconstructed baselines image with marks of line segments. If the two binary images are precisely aligned, the distortion defects can be found and located.

![Figure 9](image3.png)

**Figure 9.** The testing binary image and corresponding reconstructed baselines image with marks of line segments.

### 3.3 Comparisons of image differences

For comparing the differences between the testing binary image and the reconstructed baselines image, we use image subtraction to obtain the resulting image expressed as follows,

\[
re(x,y) = bw(x,y) - f'(x,y)
\] (6)

where \(bw(x,y)\) is a binary image, \(f'(x,y)\) is a reconstructed baselines image, and \(re(x,y)\) is the resulting image that indicates the locations of detected distortion defects.

### 4 Experiments and analyses

To evaluate performance of the proposed approaches, experiments were conducted on real curved car glass,
provided by a car windshield manufacturing company. All samples were randomly selected from manufacturing process of car glass. Testing images (40) of the curved car glass, of which 10 have no distortion defects (normal samples) and 30 have various transmitted distortion defects (defective samples), were tested. Each image of the surface has a size of 256 × 256 pixels and a gray level of 8 bits. The proposed distortion defect detection algorithm is edited in Matlab language and executed on the 7th version of the MATLAB interactive environment (data analysis, algorithm development, and model creations and applications). The system is implemented on a personal computer with CPU Inter (R) Core(TM) i5-3230M and 8 GB RAM.

4.1 Detection results for two severity levels of distortion defects

This study proposes a Hough transform based approach to inspect transmitted distortion defects on curved car glass. Figure 10 shows the initial and resulting images of the testing samples with serious and minor distortion defects. It indicates that not only the serious distortion defects but also the minor defects can be detected by the proposed method under proper parameter selection.

![Figure 10. The initial and resulting images of testing samples with serious and minor distortion defects.](image)

4.2 Detection results for standard patterns with different numbers of line segments

In the previous experiments, the standard pattern with 7 line segments is used to project the line pattern on testing images through the transmission of transparent glass. If we change the standard patterns with different numbers of line segments, the detection results of distortion defects will be different. The more line segments in a standard pattern, the more accuracy to present the deformation level in a testing image. We use different standard patterns with three numbers of line segments, 6, 7, and 8, to quantify the deformation of a car glass due to distortion defects. Figure 11 shows the initial, processed, and resulting images by the proposed method for the three standard patterns with different line segments. From the comparison of the resulting images, the detection result using the standard pattern with 7 line segments has better inspection performance because of less false alarms.

![Figure 11. The initial, processed, and resulting images by the proposed method for standard patterns with different numbers of line segments.](image)

4.3 Overall performance index of detection results for distortion defects

To present the overall detection performance of distortion defects in the testing samples, an index $CR$, called distortion defect ratio, is defined as follows,

$$CR = \frac{\text{total}_re}{\text{total}_f}, \tag{7}$$

where the $\text{total}_re$ is the pixel number of detected distortion defects in a resulting image, and the $\text{total}_f$ is the pixel number of line segments in a reconstructed baselines image. The $CR$ value is the ratio of detected distortion pixels to reconstructed baselines pixels and it locates between 0 and 1. This index indicates the deformation level of a testing image. The larger the index, the worse the distortion degree. Figure 12 shows the distribution of distortion defect ratios in the 40 testing samples. We find the samples 1 to 20 have serious distortion defects, the samples 21 to 30 have minor distortion flaws, and the samples 31 to 40 are normal based on the judgments of magnitudes of the $CR$ values.

![Figure 12. The distribution of distortion defect ratios in 40 testing samples.](image)
5 Conclusions

This study proposes a novel approach based on Hough transform scheme to inspect transmitted distortion defects on curved car glass. To quantify the deformation of a car glass, a standard pattern with vertical lines transmitted on a testing glass is captured as a testing image. The testing image is transformed to Hough domain to obtain the coordinates of the correct axis positions of multiple vertical lines. Through the accumulator analysis to find the peak points of the vertical lines in Hough domain, an image with new vertical lines is reconstructed from the selected peak points by taking the inverse Hough transform. Then, the binary testing image subtracts the reconstructed baselines image to obtain a binary difference image of distortion defects. Finally, the cumulated deviation ratios of distorted segments are calculated and the offset pixel ratio of distortion segments reveals the level of distortion in the image. Experimental results show that the proposed method effectively determines whether there are distortion flaws with the occurrence location, as well as distortion segment cumulative pixel ratio.

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7 References