Automated Distortion Defect Inspection of Curved Car Mirrors Using Computer Vision

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Abstract – Currently, the curved mirrors have been widely used in vehicle rearview mirrors and security mirrors on the driving roads and make drivers have better fields of views and driving information. In the production process of curved car mirrors, mirrors with reflected distortion defects result from the unstable temperature changes of ovens and inappropriate control of over-flow fusion process. It is not easy to measure the magnitudes of distortion defects on curved car mirrors. This study proposes a novel approach based on small-shift process control schemes to inspect reflected distortion defects on curved car mirrors. We first detect the intersection points of the standard reflected pattern, then measure the distances of the intersection points from the origin (center point), and calculate the distance deviations of the corresponding intersection points between the defective and normal images. Finally, we apply the cumulative sum (CUSUM) and EWMA control methods to judge the existence of the distortion defects based on the accumulative deviation distances.

Keywords: Industrial inspection; curved car mirrors; distortion defects; computer vision system; small-shift control scheme.

1 Introduction

Comparing with plane car mirrors, curved car mirrors have the characteristics of higher reflectance and wider field of view. Currently, the curved mirrors have been widely used in vehicle rearview mirrors and security mirrors on the driving roads and make drivers have better driving information. Since the reflected distortion defects and surface defects directly affect the display quality of car mirrors, the detection of the kinds of defects is very important for car mirror manufacturers. In the production process of curved car mirrors, mirrors with reflected distortion defects result from the unstable temperature changes of ovens and inappropriate control of over-flow fusion process. 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 mirrors. Furthermore, the curved mirrors with the property of higher reflection increase the difficulty of discrimination of the distortion defects on car mirrors. Therefore, this research aims at exploring the automated visual inspection of reflected distortion defects of the curved car mirrors.

The defective car mirrors with distortion defects providing shape-distorted scene information may lead car drivers making wrong decisions when driving. Figure 1 shows the normal and defective images of curved car mirror surfaces with reflection of street scene. The object shapes reflected in the defective image are significantly distorted. The mirror distortion defects may make reflected objects look irregularly, out of focus, and blurry in the defective images. These distorted images may result in making wrong judgment by car drivers and lead to dangerous car accidents.

![Figure 1. The curved car mirror images with reflection of street scene: (a) a normal image; (b) a defective image with distortion defect.](image)

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. Furthermore, difficulties also exist in precisely inspecting distortion defects by 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 reflected patterns, and so on.

Current automated computer vision system (off-line and sampling) uses a concentric circle pattern reflected on mirrors to acquire images and quantize distortion magnitude for selection. It is hard to precisely inspect the mirror distortion flaws by current machine vision systems due to high reflection. The property of higher reflection on curved mirrors increases the difficulty of discrimination of the distortion defects on car mirrors.
mirrors. In this research, the testing samples with length 18.1 cm, width 10.71 cm, and thickness 0.2 cm, were randomly selected from manufacturing process of car mirrors. Figure 2 shows the dimension of the testing sample and a testing sample with high reflection on mirror surface.

![Figure 2. Dimension of the testing sample and a testing sample with high reflection.](image)

This study proposes a vision system with a trapezoidal mask for image acquisition and applies cumulative sum control schemes to inspect distortion defects on curved car mirrors. To quantify the deformation (degree of distortion) of a car mirror, a inspection standard pattern (checkerboard grids) is used to reflect the pattern on a testing car mirror for image acquisition. The reflected pattern image of a defective mirror with distortion is compared with that of a normal mirror for quantifying the deformation and locating the distortion defects.

## 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]. Chiou [4] 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 from about 44% to 13.96%. Perg et al. [5] 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. Adamo et al. [6] proposed a low-cost inspection system based on the Canny edge detection for online defects assessment in satin glass. Liu et al. [7] presented the method based on watershed transform methods to segment the possible defective regions and extract features of bottle wall by rules. Then wavelet transform are used to exact features of bottle finish from images.

Many researches explored the defect detection of glass related products. Li and Tsai [8] 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 saw-mark defects in solar wafer surfaces. Lin and Tsai [9] presented a Fourier transform-based approach to inspect surface defects of capacitive touch panels. A multi-crisscross filter is designed to filter out the frequency components of the principal band regions. In the restored image, the defective region will be clearly retained. Chiu and Lin [10] applied block discrete cosine transform, Hotelling’s T-squared statistic, and grey clustering technique for the automatic detection of visual blemishes in curved surfaces of LED lenses.

Regarding the distortion correction techniques, Duan and Wu [11] proposed a new 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. Simulation results show that the method can make a good correction of the coordinate position and gray value. Zhang et al. [12] presented a distortion-correction technique that can automatically calculate correction parameters, without precise knowledge of horizontal and vertical orientation. The method is applicable to any camera-distortion correction situation. Based on a least-squares estimation, the proposed 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. The distortion correction coefficients are obtained by the least-squares estimation technique. 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 has been employed for assisting with the data collation and organization needed for implementation of neural network training. The neural network was developed for modelling the error in the measured location of image features such as a matrix of dots.

Most of the distortion related works focus on the distortion correction of optical lenses. Most of the automated inspection systems of glass and mirrors mainly detect surface defects and the distortion defect is not included. It is difficult to precisely detect reflected distortion defects embedded on surface of curved car mirrors with high reflection. Currently, there are very few literatures on inspection of mirror distortion defects using automated visual inspection system. In this research, a small-shift control scheme based vision system is proposed to detect reflected distortion defects on curved mirrors.

## 3 Proposed method

To quantify the deformation (degree of distortion) of a car mirror, this research proposes a inspection standard pattern (checkerboard grids) to reflect the pattern on a testing car mirror for image acquisition. The reflected pattern image of a defective mirror with distortion is compared with that of a
normal mirror for quantifying the deformation and locating the distortion defects. Firstly, we detect the intersection points of the inspection standard pattern, then measure the distances of the intersection points from the origin, and calculate the distance deviations of the corresponding intersection points between the defective and normal images. Finally, we apply the small-shift control schemes to judge the existence of the distortion defects based on the detection of the slight changes of the distance deviations.

3.1 Image acquisition

To clearly capture images with proper reflection for further process, this study proposes a vision system with a trapezoidal mask for image acquisition shown in Figure 3. The testing sample is put in the bottom of the mask and the standard pattern is attached on the top inside the mask. Figure 4 shows the three-view drawings of the trapezoid mask and the specifications of the standard concentric circle pattern. To acquire the images with proper reflected intensity, the control of lighting environment is very important. Figure 5 demonstrates the image acquisition with trapezoidal mask and light sources: (a) the captured image without light sources; (b) the captured image with proper light sources.

![Figure 3. The proposed vision system with a trapezoidal mask for image acquisition.](image)

3.2 Image process procedures

The captured testing image will be processed in several steps. Figure 6 shows the results and differences performed the proposed approach for detecting distortion defects in curved car mirrors. Figure 6(a) and (b) present the captured testing image and the corresponding gray level image using the checkerboard pattern. Figure 6(c) depicts the binary image that the Otsu method applied to do segmentation. Figure 6(d) describes the feature extraction of the feature points in the checkerboard pattern and the cumulative sum charts of the small-shift detection method. And, Figure 6(e) is the resulting image that show the detected distortion defects in red by the proposed detection method. The results reveal that the slight distortion defects in curved mirror surface are correctly separated in the binary image, regardless of insignificant distortion differences.

![Figure 4. (a) Three-view drawings of the trapezoid mask; (b) Specifications of the standard checkerboard pattern.](image)

![Figure 5. Image acquisition with trapezoidal mask and light sources: (a) the captured image without light sources; (b) the captured image with proper light sources.](image)

![Figure 6. Procedures of the image process flow by the proposed method.](image)

3.3 Standard concentric circle pattern

A standard concentric circle pattern includes 6 concentric circles in this study. Figure 7(a) shows the definition of the feature points in the concentric circle pattern and Figure 7(b) illustrates the coordinates of 8 intersection points on the innermost concentric circle. For each of the 6 concentric circles, 8 intersection points are \( I_{ij} \) with coordinates \((x_{ij}, y_{ij})\) and the feature values are the distances \( d_{ij} \) between the intersection points and center point of the concentric circles. The center point \( O(x, y) \) is determined by the 8 intersection points of the innermost circle:
\[
O(x, y) = \left( \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} x_{i,j}, \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} y_{i,j} \right)
\]

where \( m = 1, n = 8 \).

The feature values \( d_{i,j} \) are the distances calculated from \( O(x, y) \) and \( I_{i,j}(x_{i,j}, y_{i,j}) \), correspondingly:

\[
d_{i,j} = \sqrt{(x_{i,j} - x)^2 + (y_{i,j} - y)^2}
\]

The distances of a testing image will be compared with those of a normal image to measure the deviations of the corresponding distances for detecting the distortion defects.

**Figure 7.** (a) Definition of the feature points in the concentric circle pattern; (b) The coordinates of 8 intersection points on the innermost concentric circle.

### 3.4 Standard checkerboard grid pattern

A standard checkerboard grid pattern includes 3 concentric squares in this study. Figure 8(a) shows the definition of feature points in the checkerboard pattern and Figure 8(b) illustrates the coordinates of 12 intersection points on the innermost concentric square. For the 3 concentric squares, 60 intersection points are \( I_{i,j} \) with coordinates \((x_{i,j}, y_{i,j})\) and feature values are distances \( d_{i,j} \) between the intersection points and center point \( O(x, y) \) of the concentric squares. The center point \( O(x, y) \) is determined by 12 intersection points of the innermost square:

\[
O(x, y) = \left( \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} x_{i,j}, \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} y_{i,j} \right)
\]

where \( m = 1, n = 12 \).

The feature values \( d_{i,j} \) are the distances calculated from \( O(x, y) \) and \( I_{i,j}(x_{i,j}, y_{i,j}) \), correspondingly:

\[
d_{i,j}(x_{i,j}, y_{i,j}) = \max(|x - x_{i,j}|, |y - y_{i,j}|)
\]

Similarly, the distances of a testing image will be compared with those of a normal image to measure the deviations of the corresponding distances for detecting the distortion defects.

**Figure 8.** (a) Definition of feature points in the checkerboard pattern; (b) The coordinates of 12 intersection points on the innermost concentric square.

### 3.5 Small shift control schemes - CUSUM methods

We measure the distances of the intersection points from the origin, and calculate the distance deviations \( \Delta d_{i,j}(\Delta d_{i,j} = d_{i,j} - \overline{d}_{i,j}) \) of the corresponding intersection points between the testing image \( (d_{i,j}) \) and normal image \( (\overline{d}_{i,j}) \). The small-shift control schemes is applied to detect the slight changes of the distance deviations for detecting distortion defects.

#### 3.5.1 Tabular CUSUM method

To detect slight changes in the distance deviations, this research proposes the CUSUM algorithm, which is commonly used in statistical process control to detect the slight shift or deviation from the normal production process [15, 16]. Generally, the CUSUM method processes data, that are smooth in the beginning periods and that deviate slightly in the later periods. The cusan scheme works by accumulating derivations from 0 that are above target with one statistic \( s_C \) and accumulating derivations from 0 that are below target with another statistic \( s_C \). The statistics \( s_C \) and \( s_C \) are called one-sided upper and lower CUSUMs (cumulative sum), respectively. They are computed as follows:

\[
C_i^+ = \max\left(0, \Delta d_{i,j} - (\mu_0 + K) + C_{i-1}^+\right)
\]

\[
C_i^- = \max\left(0, (\mu_0 - K) - \Delta d_{i,j} + C_{i-1}^-\right)
\]

where \( C_0 = C_0 = 0, K = (\delta / 2) \sigma \).

In Eqs. (5) and (6), \( K \) is usually called the reference value, and it is often chosen about halfway between the target \( \mu_0 \) and the out-of-control value of the mean \( \mu_t \) that we are interested in detecting quickly. Thus, if the shift is expressed in standard deviation units as \( \mu_t = \mu_0 + \delta \sigma \), then \( K \) is half the magnitude of the shift.
\[ K = \frac{\delta}{2} \sigma = \frac{|\mu_h - \mu_0|}{2} \Rightarrow \delta \sigma = |\mu_i - \mu_0| \Rightarrow \delta = \frac{|\mu_1 - \mu_0|}{\sigma} \]  

Note that \( C_i^+ \) and \( C_i^- \) accumulate deviations from the target value \( \mu_0 \) that are greater than \( K \), with both quantities reset to zero on becoming negative. When either \( C_i^+ \) or \( C_i^- \) exceeds the decision interval \( H \), the sample set is considered out-of-control. A reasonable value for \( H \) is five times the standard deviation \( \sigma \) [17].

### 3.5.2 Standardized CUSUM method

Two advantages of the standardized Cusum scheme, the choices of the parameters \( k \) and \( h \) do not depend on standard deviation. The other is the standardized Cusum scheme leads naturally to a cusum for controlling variability [17]. The standardized Cusums are defined as:

\[ y_i = \frac{x_i - \mu_0}{\sigma} \]  

\[ C_i^+ = \max \{0, y_i - k + C_{i-1}^+\}, \quad C_i^- = \max \{0, -k - y_i + C_{i-1}^-\} \]

where the initial values \( C_i^+ = C_i^- = 0 \), \( i = 0 \).

### 3.6 Small shift control scheme - EWMA method

The exponentially weighted moving average (EWMA) control method is also a good alternative in detecting small shifts [17, 18]. The exponentially weighted moving average \( Z_i \) is defined as:

\[ Z_i = \lambda x_i + (1 - \lambda) Z_{i-1} \]

where \( 0 < \lambda \leq 1 \) is a constant and the starting value is the process target \( Z_0 = \mu_0 \). The values of the parameter \( \lambda \) smoothing constant or called weight in the interval 0.05–0.25 work well in practice. A good rule of thumb is to use smaller value of \( \lambda \) to detect smaller shifts. The control limits for the EWMA control method are as follows:

\[ UCL_i = \bar{X} + L \sigma \sqrt{\frac{\lambda}{2 - \lambda}} [1 - (1 - \lambda^2)] \]  

\[ LCL_i = \bar{X} - L \sigma \sqrt{\frac{\lambda}{2 - \lambda}} [1 - (1 - \lambda^2)] \]

The design parameters of the chart are the multiple of sigma used in the control limits (\( L \)) and the value of \( \lambda \). The performance of the EWMA control scheme is approximately equivalent to that of the CUSUM method, and in some ways it is easier to set up and operate.

### 4 Experiments and analyses

To evaluate performance of the proposed approaches, experiments were conducted on real curved car mirrors, provided by a car mirror manufacturing company. All samples were randomly selected from manufacturing process of car mirrors. Testing images (386) of the curved car mirrors, of which 136 have no defects and 250 have various reflected distortion defects, were tested. Each image of the surface has a size of 256 × 256 pixels and a gray level of 8 bits. The mirror 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 Core 2 Duo 2.33 GHz and 2GB D-RAM.

The higher the performance evaluation indices, \((1 - \alpha)\) and \((1 - \beta)\), the more accurate the detection results. Statistical type I error \( \alpha \) suggests the probability of producing false alarms, i.e. detecting normal regions as distortion defects. Statistical type II error \( \beta \) implies the probability of producing missing alarms, which fail to alarm real distortion defects. Area of normal region detected as distortion defects is divided by the area of actual normal region to obtain type I error, and the area of undetected distortion defects by the area of actual distortion defects to obtain type II error. Correct classification rate \((CR)\) is defined as: 

\[ CR = \frac{N_c + N_{d1}}{N_{total}} \]

where \( N_c \) is the pixel number of normal textures detected as normal areas, \( N_{d1} \) is the pixel number of real distortion defects detected as defective regions, and \( N_{total} \) is the total pixel number of a testing image.

As the decision threshold value changes, so do its false alarm rate \((\alpha)\) and detection rate \((1 - \beta)\), both of which are used to describe the performance of a test according to hypothesis testing theory [19]. When various decision thresholds are used, their pairs of false alarm rates and detection rates are plotted as points on a Receiver Operating Characteristic (ROC) curve. The upper-left corner indicates a 100% detection rate and a 0% false alarm rate. The more the ROC curve approaches the upper-left corner, the better the test performs. In industrial practice, a more than 90% detection rate and a less than 10% false alarm rate are a good rule of thumb for performance evaluation of a vision system.

The choices of the parameters \( k \) and \( h \) determine the control limits of the cumulative sum schemes. Table 1 shows the parameter settings and performance evaluation of the two cumulative sum schemes. Figure 9 demonstrates the ROC curve of the proposed CUSUM methods with different parameter settings of \( k \) and \( h \) values, respectively. It shows the defect detection performance of the standardized CUSUM method with parameter settings \((k,h)\) values of \((1.5, 5), (1.5,\)
or (1.75, 4) is better than those of the Tabular CUSUM method with parameter settings \((k, h)\) values of (2.25, 4.6) or (2.25, 4.8). Similarly, the selections of the parameters \(\lambda\) and \(L\) decide the control limits of the EWMA method. Figure 10 shows the ROC curve of the proposed EWMA method with different parameter settings of \(\lambda\) and \(L\) values, respectively. It indicates the defect detection performance of the EWMA method with parameter settings \((\lambda, L)\) values of (0.8, 4) has the best detection result with false alarm rate 4.41% and defect detection rate 98%. Accordingly, an appropriate approach and good parameter settings, with its ROC curve closest to the upper-left corner, outperforms the other methods. This implies that the more accurate parameter settings of the small-shift detection approaches are selected, the better the defect detection results will have.

**Table 1.** Parameter settings and performance evaluation of the two cumulative sum schemes.

<table>
<thead>
<tr>
<th>Parameter Evaluation</th>
<th>Tabular CUSUM</th>
<th>Standardized CUSUM</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>5.88%</td>
<td>5.88%</td>
</tr>
<tr>
<td>(1-\beta)</td>
<td>95.60%</td>
<td>98.00%</td>
</tr>
<tr>
<td>Parameter</td>
<td>(k=2.25)</td>
<td>(k=1.5 \cdot h=5.2)</td>
</tr>
<tr>
<td></td>
<td>(h=4.6 \cdot 4.8)</td>
<td>(k=1.75 \cdot h=4)</td>
</tr>
</tbody>
</table>

**Figure 9.** ROC curves of CUSUM methods.

The current visual inspection method uses the concentric circle pattern as the inspection standard pattern to measure the magnitudes of distortion defects on curved car mirrors. For the concentric circle pattern, we calculate the distortion rate \(\%\):

\[
\% = \left( \frac{d_{ij} - \overline{d}_i}{d_{ij}} \right) \times 100\%
\]

where \(d_{ij}\) is the distance between the intersection point \(I(i, j)\) and the center point \(O(x, y)\), \(\overline{d}_i\) is the average of the distances of the 8 intersection points on the same concentric circle \(i\).

\[
\overline{d}_i = \frac{d_{i1} + d_{i2} + \cdots + d_{i8}}{8}
\]

For a normal curved mirror, the distortion rate \(\% \leq 3.8\). And, for a normal plane mirror, the distortion rate \(\% \leq 1.7\). If the distortion rate of a testing curved mirror image is more than 3.8%, we can conclude that some distortion defects exist in the image. Table 2 shows the parameter settings and performance evaluation of the current visual inspection method. The current method achieves the best detection result with false alarm rate 4.41% and defect detection rate 98% when the threshold of distortion rat 1.15 is applied.

**Table 2.** Parameter settings and performance evaluation of the current visual inspection method.

<table>
<thead>
<tr>
<th>Control limits</th>
<th>1</th>
<th>1.05</th>
<th>1.1</th>
<th>1.15</th>
<th>1.2</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>8.09%</td>
<td>8.09%</td>
<td>5.15%</td>
<td>4.41%</td>
<td>2.94%</td>
</tr>
<tr>
<td>(1-\beta)</td>
<td>93.20%</td>
<td>92.40%</td>
<td>90.80%</td>
<td>90.80%</td>
<td>88.40%</td>
</tr>
<tr>
<td>Control limits</td>
<td>1.25</td>
<td>1.3</td>
<td>1.35</td>
<td>2.5</td>
<td>3.8</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>2.21%</td>
<td>2.21%</td>
<td>2.21%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>(1-\beta)</td>
<td>84.40%</td>
<td>82.40%</td>
<td>81.60%</td>
<td>39.20%</td>
<td>31.60%</td>
</tr>
</tbody>
</table>

To compare the performance of the mirror distortion defect detection, Table 3 summarizes the detection results of our experiments. Three small-shift detection approaches and two traditional techniques are evaluated against the results by professional inspectors. The average defect detection rates \((1 - \beta)\) of all testing samples by the five methods are, respectively, 95.6% (Tabular CUSUM method), 98.0% (Standardized CUSUM method), 98.0% (EWMA method), 95.55% (Shewhart method) [17], and 90.8% (current method). However, the two small-shift CUSUM methods have slightly higher false alarm rates \((\alpha)\), 5.88% (Tabular CUSUM method) and 5.88% (Standardized CUSUM method). On the contrary, the other small-shift detection approach has rather lower false alarm rate, 4.41% (EWMA method). The proposed EWMA method has higher correct classification rates \((CR)\) than do the other methods applied to distortion defect detection of curved car mirror images. The average
computation time for processing an image of 256 × 256 pixels is as follows: 2.10 seconds by Tabular CUSUM method, 2.13 seconds by Standardized CUSUM method, 1.97 seconds by EWMA method, and 1.10 seconds by the current method. Hence, the proposed small-shift EWMA method can overcome the difficulties of detecting distortion defects on curved car mirrors and excels in its ability of correctly discriminating slight distortion defects from normal regions.

Table 3. Summarized comparison table of distortion defect detection of curved car mirrors for five different methods.

<table>
<thead>
<tr>
<th></th>
<th>Tabular CUSUM (k=2.5, l=0.3)</th>
<th>Standardized CUSUM (k=1.5, l=0.3)</th>
<th>EWMA (k=1.6, l=0.3)</th>
<th>Shewhart (L=4)</th>
<th>Current Visual Inspection System (Distortion rate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(z)</td>
<td>5.88%</td>
<td>5.88%</td>
<td>4.41%</td>
<td>3.20%</td>
<td>4.41%</td>
</tr>
<tr>
<td>(1-β)</td>
<td>95.60%</td>
<td>98.00%</td>
<td>98.00%</td>
<td>95.55%</td>
<td>90.8%</td>
</tr>
<tr>
<td>Time (Sec.)</td>
<td>2.1005</td>
<td>2.1324</td>
<td>1.9724</td>
<td>1.4642</td>
<td>1.1006</td>
</tr>
</tbody>
</table>

5 Conclusions

This study proposes a spatial domain approach based on small-shift control schemes to inspect reflected distortion defects on curved car mirrors. To quantify the deformation of a car mirror, a standard checkerboard pattern is designed to reflect the pattern on a testing car mirror for image acquisition. The reflected pattern image of a defective mirror with distortion is compared with that of a normal mirror for quantifying the deformation and locating the distortion defects by small-shift control schemes. Experimental results show that the proposed EWMA control scheme achieves a high 98.00% probability of correctly discriminating distortion defects and a low 4.41% probability of erroneously detecting normal images as defective ones on curved car mirror images. The further research is to extend the proposed method to judge the severity levels of the surface distortion defects (e.g., very serious, serious, moderately serious, minor, etc.) and apply the proposed method to inspect transparent glass with different surface distortion defects.

6 Acknowledgment

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7 References


