Research on Intelligent Image Recognition Technology Based on Equalization Algorithm

Qin Fang, Zeng Weijia*, Liu Ruijie, Lu Xuming
Dalian University of Technology
1850508590@qq.com

Abstract. In the image edge distortion correction, the straight-line projection-derived edge fit is poor, resulting in large correction errors. Therefore, an image edge distortion correction algorithm based on the equalization algorithm is proposed in the paper, where the adaptive threshold wavelet denoising algorithm is adopted to implement adaptive transformation of various scale parameters to complete noise removal. According to the results of image denoising, Fisher vector coding is used to optimize the results of the equalization algorithm to extract the edge distortion of the image. Besides, based on the edge distortion shape extraction results, the correction objective optimization function is obtained to analyze the edge fracture situation, realizing the linear projection derivative edge fitting. Meanwhile, by determining the image edge error evaluation function, the method of image edge distortion correction is judged to achieve the purpose of image edge distortion correction. Therefore, taking noisy barrel distortion and pincushion distortion images as the research object, the experimental analysis is carried out. The results show that the algorithm proposed in the paper can effectively correct the barrel distortion and pincushion distortion of the image, achieving high-precision and high-efficiency image edge distortion correction.

1. Introduction
In order to obtain image information with a larger field of view, in most applications where a camera is used, a wide-angle lens is necessary [1]. Wide-angle lenses are mostly used in vehicle monitoring in the traffic field. The driver can determine the safe driving distance by observing the shooting results of the wide-angle lens, which can improve driving safety. However, the image obtained by the wide-angle lens will have a certain level of edge distortion, which will affect the observation effect [2]. Therefore, it is necessary to implement edge distortion correction on the obtained wide-angle image to assist the observer to implement image observation with high efficiency and high precision [3]. Furthermore, it is of significance to study an efficient image edge distortion correction algorithm [4].

Nowadays, there are mainly two image edge distortion correction algorithms. One is an optical correction algorithm with an improved lens structure, and the other is a correction algorithm through digital image processing. The digital image processing correction algorithm completes the image edge distortion correction in the post-processing. After obtaining the distorted image, the image processing algorithm and other mathematical knowledge are applied to correct the edge distortion image [5]. Compared with the optical correction algorithm, the digital image processing correction algorithm has no complicated lens structure and more cost investment. However, the correction results of the above two algorithms are not ideal, which are difficult to obtain a clear corrected image. Therefore, an image edge distortion correction algorithm based on the equalization algorithm is proposed in the paper to provide a valuable reference for the image edge distortion correction.
2. Research on Image Edge Distortion Correction Algorithm

2.1. Wavelet Image Denoising

The process of wavelet image denoising algorithm based on adaptive threshold is as follows:

1. Multi-scale decomposition of the image is implemented through wavelet transform.
2. Calculate noise variance $\rho^2$:
   $$\rho^2 = \left[ \frac{\text{Median}(X_{j,p})}{0.6745} \right]^2$$
   Among them, $X_{j,p} = \text{subband}_{pp}$, $pp_1$ refers to sub-band.
3. Calculate the scale parameter $\gamma$ at all levels:
   $$\gamma = 2^{-i} \sqrt{\log \left( \frac{K_i}{U} \right) \rho^2}$$
   Among them, $i = 1,2,...,I$, $K_i$ represents the length of the $t$-level sub-band in the image, and $U$ refers to the total value of the number of decomposition layers. With the change of $i$, the scale parameters at all levels will be adaptively transformed $^6$.
4. Calculate the standard deviation $\rho_x$ of the high-frequency coefficients from 1 to $U$.
5. Calculate threshold $W$:
   $$W = \frac{2\rho_x^2}{\rho^2}$$
   Meanwhile, the high-frequency coefficients of the 1 to I layers are thresholded and filtered. The wavelet coefficients after thresholding are used to filter the image signal to obtain the denoised image signal $^7$.

For the wavelet coefficients of non-single-layer decomposition, the more layers there are, the smaller the noise energy will be. In addition, due to the adaptability of the threshold, each layer of noise and image effective information will be separated $^8$.

2.2. Equalization Algorithm Improvement and Distortion Shape Extraction

Since the image feature extraction results of traditional encoding in the equalization algorithm have large errors, the encoding method in the equalization algorithm needs to be improved. Therefore, Fisher vector encoding is used to accurately extract image features to obtain accurate edge distortion shape extraction results and improve distortion correction.

Assuming there are $M$ training images $\{a_j\}_{j=1}^M$, the block size and step size are respectively set as $t_1 \times t_2$ and $z_1 \times z_2$. Then image information is obtained according to the block size and step size of the $j$th sub-image:

$$Z_j = W \sum_{i=1}^M \mu(t_1 \times t_2) + \mu(z_1 \times z_2)$$

Among them, $\mu$ represents the limiting factor of the image size.

According to the calculation results of image information, the local features of all the block images in all training image sets are calculated to establish the training set after data fusion: $Z = \{Z_1, Z_2, ..., Z_{NM}\} \in S^{t_1 \times t_2} \times S^{z_1 \times z_2}$ can be seen as training set.
2.2.1. Self-encoding Training

By training a self-encoding grid, block sampling is performed on the images in the training set $S^{v_{x_{2}}}$ to obtain a training set of block images [9]. The training process includes initialization and parameter tuning of the self-encoding network. Since a non-multi-layer self-encoding network cannot use the block training set to build a network model, the multi-layer self-encoding training method can be used to implement random batch division $\{b_j\}_{j=1}^p$ on the block images.

Supposing that the parameter is 1001 to implement the restricted Boltzmann machine training process, the training batch size is set to 51 [10]. Moreover, the visible unit of each restricted Boltzmann machine runs in the interval $[0, 1.1]$. Training a higher-level restricted Boltzmann machine, when the neuron output is close to 1, it can be considered to be in the activated state, and when it is close to 0, it can be considered to be in the inhibited state. Regardless of the top layer, the hidden units of each restricted Boltzmann machine have unspecified binary situations.

If the self-encoding grid training stops, the block data set $Z$ will be vectorized to obtain $X = \{X_1, X_2, ..., X_{NM}\}$, where $X$ is obtained by transforming $Z$.

2.2.2. Fisher Vector Coding

The encoding based on the vector quantization method is a feature vector assigned only to the nearest field, which will cause larger quantization error. Meanwhile, the local constrained linear coding method adopts the optimization method of selecting the field parameter $t$ to improve the quantization accuracy. However, the application process is more complicated. Therefore, in order to accurately extract the morphological features of image edge distortion, instead of vector quantization coding, Fisher vector coding is used to obtain the optimal image edge features.

The Gaussian mixture model is first implemented on the training set $X$ to obtain the feature mean $c_j$:

$$c_j = \frac{1}{N(Z_j)} \sum_{j=1}^{M} X \cdot \Delta \tau_j(t)(1 - \mu)$$  \hspace{1cm} (5)

Among them, $\Delta \tau_j(t)$ represents the Gaussian mixture probability density function.

According to the obtained mean value, the training $X$ is projected to the feature space through nonlinear mapping to construct the covariance matrix $\text{cov}(X)$:

$$\mathcal{G}: X \rightarrow \text{cov}(X) \in S^{v_{x_{2}}}$$  \hspace{1cm} (6)

Among them, $\mathcal{G}$ refers to the nonlinear mapping function.

Finally, Fisher vector coding is implemented on the constructed covariance matrix to obtain the feature vector.

2.2.3. Distortion Shape Extraction

After completing the auto-encoding training and Fisher vector encoding, multi-scale analysis of the feature vector is used to extract the distortion shape. The specific process is as follows:

(1) Block images of multiple scales are selected to implement self-encoding training and encoding and classification of image edge samples are performed based on various scales;

(2) The prediction probability $Q_{i,j}$ is calculated, which describes the probability that the $j$th image edge sample belongs to the $j$th category (distortion):

$$Q_{i,j} = u_i \log_2(1 + \frac{p_i^j D_i^j}{\epsilon^2})$$  \hspace{1cm} (7)
Among them, \( u_i \) represents the feature vector, \( p^i_j \) refers to the probability attribute function of the \( i \)th type of distortion, and \( D^j_i \) indicates the change function of the \( j \)th image with the \( i \)th type of distortion. \( \varepsilon \) is the distortion membership error.

Assuming that \( T \) different block sizes are used to perform \( M \) classifications, the probability prediction model \( T \times M \) obtained by stitching is set as a classifier for image edge distortion feature training, and the output result of the classifier is the extraction result of image edge distortion shape.

2.3. Image Edge Distortion Correction Algorithm

Based on the image edge distortion shape extraction results obtained in section 2.2, the image edge distortion correction algorithm is studied. In order to make the correction result optimal, the objective optimization function needs to be constructed:

\[
E_{co} = \sum_{j=1}^{M} k_j \cdot M \{Z_1 : Z_n\}
\]  

Among them, \( k_j \) represents the distortion correction optimization parameter.

In the implementation of distortion correction, when the objective optimization function is constant, the image distortion may be less than one pixel, and there will be edge fractures, as shown in Figure 1:

![Figure 1 Schematic diagram of edge line connection](image)

In Figure 1, the edge line segments \( A_1 \) and \( A_2 \) are broken, and \( A_3 \) and \( A_4 \) represent interference items. By setting the threshold \( F \) and the angle threshold \( \kappa \), it is judged whether the two adjacent edges are connected. If the distance \( e \) between the endpoints of the two edge segments is less than \( F \), and the angle \( \beta \) between the two edge segments is less than \( \kappa \), then the two edge segments are connected.

Generally speaking, there is less distortion effective information in the shorter line segment, which contains a certain amount of noise. Therefore, such short line segments are regarded as outliers. Moreover, in the three-dimensional space of the lens, the edge with small curvature is usually used as the edge derived from linear projection, so the edge derived from such small curvature curve projection is also regarded as an outlier. Additionally, for a grayscale image with a size of 767*577, the edge length threshold is set to 51 pixels. If the edge length is set as the judgment evidence, it can remove some outliers, that is, the least squares straight line fitting. The least squares straight line fitting is shown in Figure 2:
Figure 2. Schematic diagram of least squares straight line fitting

In Figure 2, the pixel point of the selected pixel of edge distortion $A_j$ to be detected is $(y_i, x_i)$, and $i=1,2,...,M$. Then, the sum of squared line segment spacing $D_j$ after edge fitting is set as the measured value of this edge distortion level. The calculation method of the sum of squares $D_j$ is:

$$D_j = Q_i \sum_{i=1}^{M} \left[ \frac{y_i(x_i-x_M) + x_i(y_M-y_i) + y_i x_M - y_M y_i}{(x_M-x_i)^2 + (y_M-y_i)^2} \right]$$

(9)

Among them, $(y_i, x_i)$ and $(y_M, x_M)$ are respectively the two endpoint coordinates.

The total value of all the edge distortion levels measured in the image is calculated, which is set as the distortion error evaluation function of the image edge, then:

$$D = \sum_{j=1}^{N} D_j$$

(10)

Among them, $N$ represents the number of distortion edges obtained by detection. If the edge is in the fitted straight line, the distortion error will be zero. The greater the curvature of the edge is, the greater the distortion error will be.

On the basis of obtaining the best distortion coefficient, the image edge distortion correction formula is constructed as:

$$C_j = \begin{cases} \frac{B_j + Q_i (E_{co} - 1)}{D > 0} \\ 0 \end{cases}, \quad D = 0$$

(11)

Among them, $B_j$ refers to the distortion correction constraint coefficient. According to the distortion error evaluation function $D$, the image edge distortion correction is performed. When $D$ is equal to 0, it means that there is no distortion. When $D$ is greater than 0, it means that there is distortion, and correction is required. In addition, on the basis of the distortion error evaluation function, the research on the image edge distortion correction algorithm is completed according to formula (11).

3. Experimental Verification

In order to analyze the effectiveness of the proposed correction algorithm, a comparative verification experiment is carried out. The image data for this experiment comes from the Caltech database of the California Institute of Technology. The Caltech database contains the Caltech101 and Caltech256 data sets. Each data set contains about 200 images. Moreover, there are two types of distorted pictures being tested, namely barrel-shaped and pincushion-shaped. The focal length of the lens used in the experiment is 3.0mm.
3.1. Experimental Image

In order to accurately analyze the correction performance of the proposed algorithm, the original noisy distortion of the barrel and pincushion are selected as shown in Figure 3.

(a) Barrel-shaped noisy distorted image

(b) Pincushion noisy distorted image

Figure.3 Distorted image with noise

3.2. Comparison of Correction Effects

According to the original image in Figure 3, the proposed correction algorithm, structured light image distortion correction algorithm for complex deep hole inner contour and image distortion correction algorithm based on automatic extraction of control points are verification, and the correction effects of the three algorithms on the distorted image are compared. The comparison result is shown in Figure 4-6.

(a) Barrel distortion correction results
Figure 4  Proposed algorithm correction results

(a) Barrel distortion correction results
(b) Pincushion distortion correction results

Figure 5  Correction results of structured light image distortion correction algorithm for complex deep hole inner contour

(a) Barrel distortion correction results
(b) Pincushion distortion correction results
Analyzing Figures 4-6, it can be seen that the proposed correction algorithm can effectively correct barrel-shaped distortion for two-shaped distorted images, and the corrected image is very clear. However, the distortion correction effect of the two comparison algorithms is very unsatisfactory, and the definition is poor, which is difficult to meet the application requirements of the image.

### 3.3. Comparison of Mean Square Error and Signal-to-noise Ratio

Structured light image distortion correction algorithm for complex deep hole inner contour, image distortion correction algorithm based on automatic extraction of control points and the proposed algorithm are applied to perform the correction performance comparison test, and the peak signal-to-noise ratio and the mean square error are used as the comparison indicators of the three algorithms. The calculation formula of mean square error (MSE) and peak signal-to-noise ratio (PSNR) is:

\[
MSE = \frac{1}{NM} \sum_{j=0}^{N-1} \sum_{i=0}^{M-1} (g_{ij} - g_{ref})^2
\]

\[
PSNR = 10 \log \left( \frac{256^2}{MSE} \right)
\]

\( g_{ij} \) refers to the pixel gray value of the original image, and \( g_{ref} \) represents the pixel gray value of the image after denoising.

The comparison results of the peak signal-to-noise ratio and the mean square error of the three algorithms are shown in Table 1.

| Noise scale | Proposed algorithm | Distortion correction algorithm for structured light image of complex deep hole inner contour | Image distortion correction algorithm based on automatic extraction of control points |
|-------------|--------------------|---------------------------------------------------------------------------------|---------------------------------------------------------------------------------|
|             | Peak signal to noise ratio | Mean square error | Peak signal to noise ratio | Mean square error | Peak signal to noise ratio | Mean square error |
| 10          | 73.9722             | 29.4402             | 220.3596             | 24.6996             | 132.3547             | 26.9135             |
| 20          | 109.5107            | 27.7363             | 262.5736            | 23.9384             | 169.7278             | 25.8334             |
| 30          | 150.8511            | 26.3454             | 295.1754           | 23.4301             | 200.8341            | 25.1025             |
| 40          | 199.1675            | 25.1387             | 319.9131           | 23.0806             | 227.7034            | 24.5572             |

Analyzing the data in the table, it can be seen that under the condition of increasing noise scale, the mean square error of the proposed algorithm is lower than that of the two comparison algorithms, and the peak signal-to-noise ratio of the proposed algorithm is higher than that of the two comparison algorithms. Therefore, it is clear the proposed algorithm has the best denoising performance.
3.4. Calibration Accuracy Comparison

Taking Figure 3 as an example, the two distorted images in Figure 3 respectively have 5 edges. After conducting denoising test on Fig. 3 with three algorithms, the accuracy after edge distortion correction is performed on them. The comparison results are shown in Table 2.

| Noise scale | Proposed algorithm | Distortion correction algorithm for structured light image of complex deep hole inner contour | Image distortion correction algorithm based on automatic extraction of control points |
|-------------|--------------------|----------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
|             | Barrel  | Pincushion | Barrel  | Pincushion | Barrel  | Pincushion |
| 10          | 5       | 5          | 5       | 4          | 5       | 5          |
| 20          | 5       | 5          | 4       | 4          | 4       | 5          |
| 30          | 5       | 5          | 4       | 4          | 4       | 4          |
| 40          | 5       | 5          | 4       | 4          | 4       | 4          |

Analyzing the data in Table 2, it is shown that under the effect of different noise scales, the proposed algorithm corrects the edge distortion of the barrel and pincushion images, and the number of edges in the image is the same as the original image, while in the image corrected by the two contrast algorithms, the number of edges is different from the original image, which is fully proved that the proposed algorithm has high correction accuracy in noisy environment.

3.5. Calibration Efficiency Comparison

In order to test the time complexity of the three algorithms, the correction time of the three algorithms in the above experiment is counted in s, which is shown in Table 3.

| Noise scale | Proposed algorithm | Distortion correction algorithm for structured light image of complex deep hole inner contour | Image distortion correction algorithm based on automatic extraction of control points |
|-------------|--------------------|----------------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
|             |                    |                                                                                       |                                                                                  |
| 10          | 0.791              | 0.922                                                                                  | 0.989                                                                           |
| 20          | 0.773              | 0.934                                                                                  | 0.983                                                                           |
| 30          | 0.742              | 1.013                                                                                  | 1.083                                                                           |
| 40          | 0.791              | 0.903                                                                                  | 0.982                                                                           |
| Mean        | 0.774              | 0.943                                                                                  | 1.009                                                                           |

Analyzing the data in the table, it is shown that under different noise scales, the average time consumption of the proposed algorithm for image edge distortion correction is only 0.774s. Compared with the two comparison algorithms, the proposed algorithm takes the least time to correct and can deal with image distortion correction problems in real time.

4. Conclusion

In order to improve the effect of image edge distortion correction, an image edge distortion correction algorithm based on equalization algorithm is proposed, which only needs the spatial target with linear characteristics in the imaging field of view to obtain the distortion coefficients, so that the distortion correction objective function can be constructed to implement distortion correction. Moreover, the verification results show that the algorithm proposed in the paper is an effective image edge distortion correction algorithm. After correcting the barrel and pincushion image edge distortion, the number of edges in the image is consistent with the original image under the action of different noise scales. In addition, the time-consuming average value of the image edge distortion correction is only 0.774s. Therefore, the algorithm proposed in the paper has certain application value.
Acknowledgement
This paper is supported by "Research on data driven teaching quality evaluation system under the background of double first-class", which number is W2019003.

References
[1] Zhao Jiantang. Single image defogging algorithm based on deep learning[J]. Progress in Laser and Optoelectronics, 2019, 56(11):146-153.
[2] Wang Yu, Zhang Huanjun, Huang Haixin. Overview of image semantic segmentation algorithms based on deep learning[J]. Application of Electronic Technology, 2019, 45(6):23-27+36.
[3] Li Zhiyi, Xu Hongkai, Duan Bin. Research on image emotion feature extraction based on deep learning CNN model[J]. Library and Information Service, 2019, 63(11):96-107.
[4] Zhou Weishuo, An Bowen, Zhao Ming, et al. Heterogeneous remote sensing image registration algorithm based on geometric invariance and local similarity features[J]. Infrared Technology, 2019, 41(6):561-571.
[5] Ding Chao, Tang Liwei, Cao Lijun, et al. Structured light image distortion correction algorithm for complex deep hole inner contours[J]. Infrared and Laser Engineering, 2017, 46(12):224-230.
[6] Ma Tianjiao, Han Guangliang, Sun Haijiang. Aerial image distortion correction algorithm based on polar coordinate Lagrange interpolation[J]. Liquid Crystal Display, 2018, 33(5):418-426.
[7] Hong Yanfei, Wei Benzheng, Liu Chuan, et al. Research on automatic multi-grading of foraminal stenosis based on deep learning[J]. Journal of Intelligent Systems, 2019, 14(4):708-715.
[8] Liu Xiaqing, Zuo Qingtong, Liu Qing, et al. Deep learning denoising algorithm for cryo-EM images with ultra-low signal-to-noise ratio—DWT-CAE[J]. Small Microcomputer System, 2019, 40(6):1340-1345.
[9] Ji Chao, Huang Xinbo, Cao Wen, et al. Image salient area detection based on deep learning[J]. Progress in Laser and Optoelectronics, 2019, 56(9):125-132.
[10] Wang Wei, Zhang Tong, Wang Xin. A review of deep learning methods for image super-resolution reconstruction[J]. Small Microcomputer System, 2019, 40(9):1891-1896.