Research on Preprocessing Process for Improved Image Generation Based on Contrast Enhancement

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Abstract. Lighting conditions in daytime environments can reduce the object recognition rate by causing blurring, over-exposure, and shadows that mask important information about the object's shape and size. These phenomena also decrease the quality of image data, with outdoor quality being significantly lower than indoor quality. As deep learning-based object recognition algorithms heavily rely on image quality, a preprocessing process is required to improve the quality of learning image data and achieve high performance. To address this, the paper proposes a contrast-enhanced image generation preprocessing process that can improve image quality and mitigate the effects of poor lighting conditions.

Keywords: Contrast enhancement · CLAHE · SSIM · PSNR · LoFTR

1 Introduction

Light is one of the biggest factors that reduces the object recognition rate in an image, making it difficult to recognize the object's original objects. In particular, if the lighting conditions are bright or rough in daytime environments, the object can be blurred or over-exposed, making it difficult to distinguish the features of the object. In addition, shadows due to increased contrast from light may mask important information about the shape and size of the object. These phenomena reduce the quality of image data, and the quality is significantly lower outdoors than indoors. Deep learning-based object recognition algorithms, which mainly use images as learning data, are highly dependent on the quality of learning data, requiring a preprocessing process to improve the quality of learning image data and obtain high data quality for high performance [1–3].

This paper proposes a contrast-enhanced image generation preprocessing process to improve problems caused by lighting conditions in daytime environments and improve quality.

2 Proposed Preprocessing Process

The preprocessing process proposed in this paper can be largely divided into optimal value extraction, image generation, and quality verification stages.

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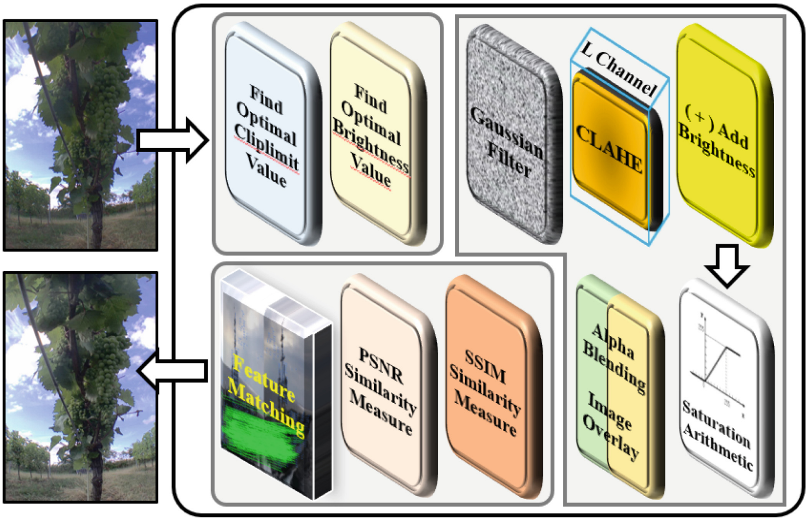

Fig. 1. Preprocessing Process

Figure 1 shows the image of the proposed preprocessing process.

Since the illumination or shadow area of the object in the image data varies depending on location, time, and environmental factors, it is necessary to find the optimal value when applying the contrast improvement technique.

Figure 2 is an object image according to a change in the position of a light source. It can be seen that the illumination and shadow areas of the object are different as the position of the sun, which is a light source, changes due to changes in time factors. In this paper, CLAHE(Contrast Limited Adaptive Histogram Equation) was used as a contrast enhancement technique [4].

Fig. 2. Image of an object according to a change in position of the light source

The CLAHE algorithm, also called contrast-limited adaptive histogram equalization, is an algorithm that evenly flattens the histogram distribution level for the brightness of an image and consequently increases the contrast of the image. It has the effect of making it easier to discriminate image information with low contrast. In this paper, the createCLAHE function of the OpenCV library was used.

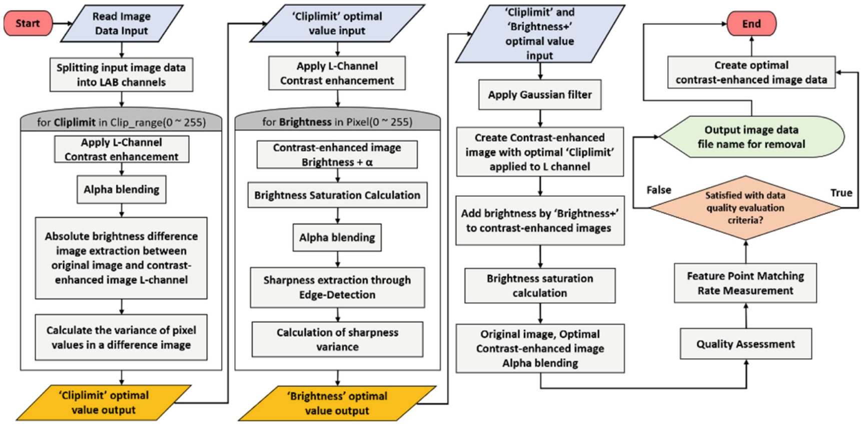

Fig. 3. Preprocessing process flowchart

Figure 3 is a flowchart of the proposal preprocessing process. It can be seen that the image improved through flowchar is created through two values (Cliplimit, Brightness) and undergoes a verification process through quality evaluation.

2.1 Extract Optimal Values

In the optimal value extraction step, the parameter 'cliplimit' is obtained with the optimal value for the contrast limit boundary value and the additional brightness to be applied to improve the shadow area. The cliplimit optimal value can calculate the absolute brightness difference between the original image and the simple CLAHE applied image, calculate the variance of the pixel value in the difference image, and specify the maximum value among the variance values repeated for the cllimit parameter range.

In the CLAHE algorithm, as the value of the parameter 'cliplimit' increases, more aggressive contrast enhancement occurs, and noise and artifacts may be excessively amplified. On the other hand, lower values may not improve contrast enough. The absolute difference in brightness between the two images indicates how much the pixel values have changed after the contrast enhancement. The variance calculation process is a measure of how spread out the pixel values are from the average value, with high variance values indicating a significant range of pixel values and low variance values indicating that the pixel values are close together. So, the value that produces the highest variance for cliplimit represents the optimal value because it represents the best balance between avoiding noise and overamplification.

Fig. 4. An example image of the absolute brightness difference between the original image and the contrast augmented image

Figure 4 is an example image showing the absolute brightness difference between the original image and the contrast enhanced image.

The optimal value for additional brightness is first edge-detection for contrast-enhanced images with cliplimit optimal values applied to calculate the variance for sharpness. The maximum value among the variance values when repeated for the pixel range 0 to 255 may be designated as an optimal value for additional brightness.

Edge Detection highlights areas of an image that have large changes or abrupt transitions in intensity between objects or areas. Because the variance for sharpness indicates how widely the sharpness values are spread throughout the image, a higher variance for sharpness is optimal because it captures both strong and subtle edges with varying levels of edge enhancement.

Figure 5 is an example image showing sharpness through edge detection.

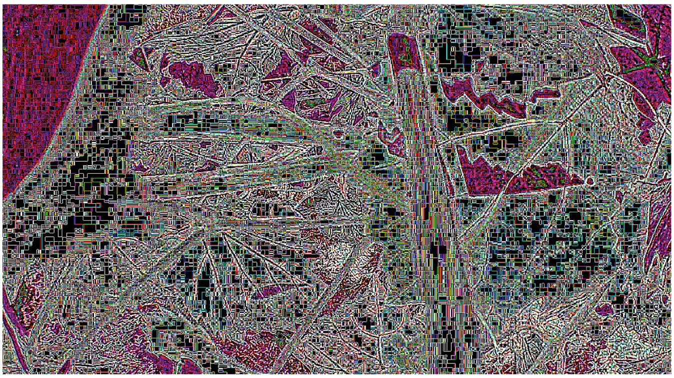

Fig. 5. Illustrative image of sharpness with edge detection

2.2 Generation an Image

When the optimal value is obtained, the following image generation process is performed. First, when the original image of the daytime environment is received, the non-uniform pixel value is adjusted evenly and Gaussian blur is processed to alleviate noise [5]. Next, a contrast improvement technique for the L (Luminosity) channel of the Lab channel is applied using the cliplimit optimal value. After increasing the brightness of the contrast-enhanced image by the optimal value, a saturation arithmetic for the contrast-enhanced image is applied. The reason for applying saturation-operation is to maintain image quality by preventing the brightness or color value of image data from changing too much [6]. Images to which saturation-operation is applied apply alpha blending with the original image to overlay the image.

Alpha blending refers to a display method that mixes the background RGB value and the RGB value above it by assigning a new value called "Alpha" to the computer's color expression value "RGB" for visual and effect when another image is overlaid on the image. Alpha blending is applied because in the case of images with simple contrast enhancement techniques, pixels are often damaged to improve contrast, resulting in noise areas, which reduce data quality [7].

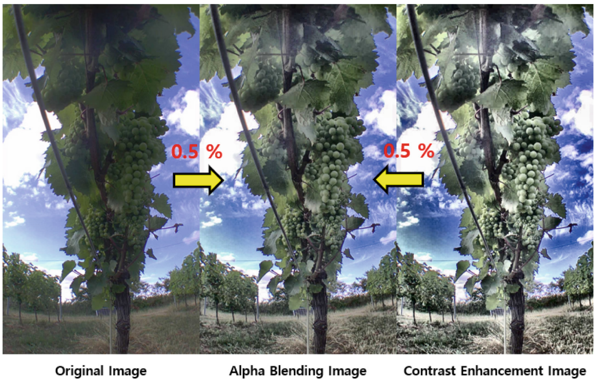

Fig. 6. Original & Alpha Blending & Contrast Enhancement Images

Figure 6 shows the original, alpha blending, and contrast enhanced images. In this paper, we applied alpha blending to the original image and the contrast improved image by specifying it as a 0.5 ratio.

Fig. 7. Result of applying preprocessing process to various daytime environment images

Fig. 8. Result of application of pretreatment process in night environment

Figure 7 is the result before and after applying the preprocessing process of this paper to various daytime environment images, and Fig. 8 is the result before and after applying the preprocessing process in the night environment. Although there is a certain degree of improvement in the night environment, it can be seen that significant noise occurs in areas without light.

2.3 Verifying the Quality of the Generated Image

In the quality verification stage, the quality of image data generated is measured through PSNR(Peak Signal-to-Noise Ratio), SSIM(Structural Simplicity Index Measure), and Feature Point Matching comparison between the original image and the generated image. PSNR represents the power of noise for the maximum power that a signal can have with the maximum signal-to-noise ratio. It is mainly used when evaluating image loss information on the front axis of image or video loss and uses decibels (db) units [8]. The formula for PSNR is as follows.

$$PSNR = 10\log\frac{S^2}{MSE} \tag{1}$$

MSE (Mean Square Error) is a mean square error that is averaged over the square of the error, and s is the maximum value of the pixel [9]. The higher the PSNR level, the lower the loss than the original image.

SSIM refers to a structural similarity index and is a method designed for evaluating human visual image quality differences, not numerical errors. The similarity of the two images is compared using three factors: luminance, contrast, and structural difference between pixel values [10]. The formula for SSIM is as follows.

$$\begin{aligned} SIM(x, y) &= l(x, y)^{\alpha} \cdot c(x, y)^{\beta} \cdot s(x, y)^{\gamma} \\ &= \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \end{aligned} \tag{2}$$

The numerical value of SSIM is between 0 and 1, and the closer it is to 1, the higher the similarity.

Feature point matching is to find similar points by comparing feature point descriptors extracted from two images, and this paper presents two methods. The first method is to detect feature points using the ORB(Oriented FAST and Rotated BRIEF) algorithm and to obtain feature point matching rates by applying the MAGSAC(Marginizing Sample Consensus) method to calculate the transformation matrix approximation for the matching point [11, 12].

The second method is to match feature points using LoFTR (Detector-Free Local Feature Matching with Transformers) [13]. Traditional local feature matching methods rely on detecting key points in an image, but this can be a tricky and computationally expensive task, especially when dealing with low-texture or repetitive areas. LoFTR, on the other hand, is a novel approach to local feature matching in computer vision using a transducer-based architecture that does not rely on explicit keypoint detection. LoFTR encodes image patch pairs into feature vectors and predicts correspondence between them, which is trained end-to-end on large datasets and achieves state-of-the-art performance on benchmark datasets. LoFTR is an innovative local feature matching solution that is particularly useful for matching images with low-textured or repetitive regions, can reduce computational costs, and can improve the accuracy of the matching process.

Figure 9 is an example image of feature point matching for two methods.

$$Accuracy = 100 \times \frac{Count(Correct\ Matching\ Points)}{Count(All\ Matching\ Points)} \tag{3}$$

When correctly matched feature points are divided by the number of matched feature points, accuracy for feature point matching can be obtained.

For 30 images (Size: 720 * 1280), an experiment was conducted to compare the performance of the process applying the two methods. The first method (using MAGSAC) took 1 min and 8 s, and the average feature matching rate was 94.5%. The second method (using LoFTR) took 4 min and 10 s, and the average feature matching rate was 99.78%.

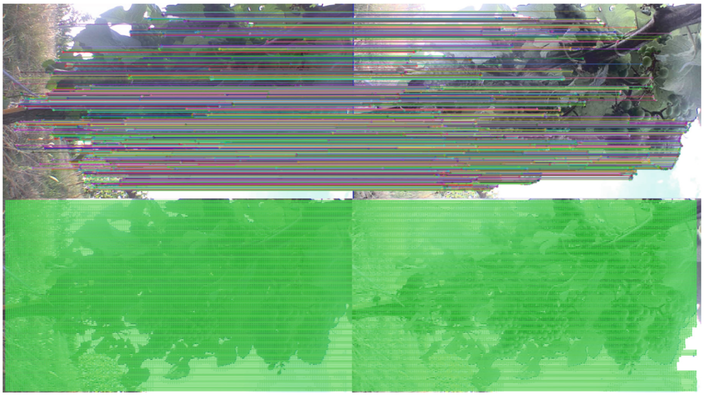

Fig. 9. Feature matching example image

3 Conclusion

In this paper, we propose an optimized contrast enhancement image generation pre-processing process in the daytime environment to improve the problems caused by lighting conditions. The preprocessing process can be divided into three stages: optimal value extraction, image generation, and quality verification. The process first obtains the optimal value of the contrast limit boundary value and the additional brightness for shadow area improvement. Then, using Gaussian-blur processing and cliplimit optimal values for input images, contrast enhancement techniques for L channels are applied, and saturation-operation is applied, and alpha-blending with the original image is applied to create an improved image. Finally, the quality of the generated image may be verified through PSNR, SSIM, and feature point matching.

When speed is more important in the feature point matching process, it is better to use the method using ORB and MAGSAC, and when high performance is required, it is better to use LoFTR. The preprocessing process proposed in this paper can be applied to various environments, not just the daytime environment, but the improvement is low for areas with little light.

In future research, we plan to conduct a comparative study on the improvement method for areas with little light during the computation process and the performance comparison of the deep learning object recognition model on the existing image dataset and the image dataset generated through the process of this paper.

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