

Article

Low Illumination Soybean Plant Reconstruction and Trait Perception

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Abstract: Agricultural equipment works poorly under low illumination such as nighttime, and there is more noise in soybean plant images collected under light constraints, and the reconstructed soybean plant model cannot fully and accurately represent its growth condition. In this paper, we propose a low-illumination soybean plant reconstruction and trait perception method. Our method is based on low-illumination enhancement, using the image enhancement algorithm EnlightenGAN to adjust soybean plant images in low-illumination environments to improve the performance of the scale-invariant feature transform (SIFT) algorithm for soybean plant feature detection and matching and using the motion recovery structure (SFM) algorithm to generate the sparse point cloud of soybean plants, and the point cloud of the soybean plants is densified by the face slice-based multi-view stereo (PMVS) algorithm. We demonstrate that the reconstructed soybean plants are close to the growth conditions of real soybean plants by image enhancement in challenging low-illumination environments, expanding the application of three-dimensional reconstruction techniques for soybean plant trait perception, and our approach is aimed toward achieving the accurate perception of current crop growth conditions by agricultural equipment under low illumination.

Keywords: three-dimensional reconstruction; image enhancement; feature detection and matching; sparse point cloud; dense point cloud



Citation: Huang, Y.; Liu, Y.; Han, T.; Xu, S.; Fu, J. Low Illumination Soybean Plant Reconstruction and Trait Perception. *Agriculture* **2022**, *12*, 2067. <https://doi.org/10.3390/agriculture12122067>

Academic Editors: Wen-Hao Su and Zhou Zhang

Received: 30 September 2022

Accepted: 25 November 2022

Published: 1 December 2022

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1. Introduction

As a new direction of current agricultural development, intelligent agriculture [1–4] not only changes the industrial model that must rely on environmental planting in traditional agriculture, but also improves the quality of agricultural products, efficiently uses various agricultural resources, achieves considerable economic and social benefits, and realizes agricultural refinement, high efficiency, and greening. Crop phenotype [5–7] is a key link in the analysis of crop growth environment, which is used to comprehensively evaluate the growth morphology and traits of crops in complex and changeable farmland environments. It is an effective way to improve the field operation of agricultural machinery and equipment. Traditional soybean plant phenotypic [8] measurement and analysis, and the manual collection of soybean plant information on the farmland are time-consuming and labor-intensive. The complex and changeable field environment and the diverse characteristics of soybean plants [9] make it difficult to obtain soybean plant phenotypic information, which increases the difficulty of accurate identification of soybean plants [10,11]. In recent years, three-dimensional reconstruction technology [12] has played an increasingly important role in the study of soybean plant phenotype. Applying three-dimensional reconstruction to the field operation of agricultural machinery and equipment, a model closer to the actual soybean plant phenotype is constructed, and the growth morphology and traits of soybean plants are evaluated quickly and efficiently. It provides

accurate information for agricultural machinery and equipment to accurately identify soybean plants, effectively solves the problems of the complex production environment in soybean fields and the diverse characteristics of soybean plants and accurate soybean plant information, and meets the important needs of refinement and high efficiency of intelligent agriculture.

The existing crop reconstruction methods mainly use two-dimensional images of crops taken from different perspectives to match by extracting features, so as to reconstruct the point cloud model of crops [13]. In practical applications, the two-dimensional images are easily constrained by illumination during the imaging process. The brightness and contrast of the acquired images are generally low and there is noise, which reduces the reconstruction accuracy of the three-dimensional morphological characteristics of crops and seriously affects the analysis of crop phenotypes. For the reconstruction of crops under low illumination, it is necessary to increase the brightness of the light. The traditional illumination brightness enhancement algorithm can be divided into the histogram equalization [14,15]-based method and the Retinex [16] theory-based method. The histogram equalization method is based on the optimization of a single pixel to achieve overall brightness and contrast enhancement, but it ignores the correlation between regional pixels and leads to the destruction of detailed information. The method based on the Retinex theory recovers image brightness and color information from image illumination information and considers the correlation of image regional features. However, for uneven illumination, it will cause color distortion and artifacts. With the significant effect of deep learning in image denoising [17] and image recognition [18], it has also been widely used in image enhancement [19]. Wei et al. [20] proposed a convolutional neural network model RetinexNet based on Retinex theory. The algorithm decomposes the input low-light image into a reflection image and an illumination image and then enhances and adjusts the image. The illumination-enhanced illumination image and the denoised reflectivity image are recombined to generate a corrected image. Zhang et al. [21] proposed a simple and effective KinD low-light image enhancement network. The network framework is similar to the RetinexNet architecture, and the core is to introduce more training loss constraints. Jiang et al. [22] introduced the GAN algorithm into image enhancement and proposed an efficient unsupervised generative adversarial network EnlightenGAN algorithm, which can be directly applied to network training without using low-light illumination or normal image blocks, with a better generalization effect. Marco Tulio Ribeiro et al. [23] proposed the LIME algorithm, which estimates the illumination of each pixel by finding the maximum value in the three channels of the RGB image. A structural prior is then applied to refine the initial image as the final illumination map to generate the final enhanced image. Lv et al. [24] proposed the MBLEN algorithm, which is a multi-branch low-light image enhancement network. By extracting rich image features from different levels for enhancement and fusing the output images generated by multiple branches, the image quality is improved from different directions.

At present, the three-dimensional reconstruction method based on SFM (structure from motion) [25] and MVS (multi-view stereo) [26] is used to obtain the three-dimensional data of the whole crop. GUAN et al. [27], using an RGB camera and a photon mixing detector (PMD), carried out three-dimensional reconstruction of soybean plants with color information and used a density-based spatial clustering algorithm (DBSCAN) to extract canopy information from the original three-dimensional point cloud. Then, principal component analysis (PCA) and an iterative closest point (ICP) algorithm were used to register multi-source images to complete the three-dimensional reconstruction of soybean plants. WANG et al. [28] constructed soybeans at different growth stages through a multi-image acquisition system based on the Kinect sensor and generated comprehensive point cloud data of soybeans from three perspectives. Conditional filtering and K-nearest neighbor filtering (KNN) algorithms were used to preprocess the original three-dimensional point cloud. Finally, random sample consensus (RANSAC) and iterative closest point (ICP) algorithms were used to complete point cloud matching and fusion. SU et al. [29] developed a

plant localization technology based on systematic crop signals for the weeds that cannot be controlled by the existing cultivation techniques in the crop row and are highly competitive with the early stage of soybean growth. By applying different concentrations of a signal compound with a unique fluorescent appearance to soybeans in different periods, the automatic detection of soybean appearance is realized, and the fluorescence images of multiple plant views are analyzed. A three-dimensional plant localization algorithm is established to accurately determine the position of soybeans in the field, which helps to perform automatic weeding tasks in weeding machines. Under low-illumination conditions, it is difficult to complete the reconstruction task by using the SFM method for the three-dimensional reconstruction of crops. When the input crop image is constrained by illumination, it will produce incorrect spatial point cloud shape estimation, inaccurate camera trajectory, and in some scenes, there is no detection of real features or pseudo-features that cannot be matched with features in other images. Aiming at the accurate phenotypic information of soybean plants obtained by agricultural machinery and equipment in the environment of insufficient illumination, this paper proposes the reconstruction and trait perception of soybean plants under low illumination. With soybean plants as the center, the camera is used to collect the images of soybean plants under low illumination in an orderly manner. Through the EnlightenGAN image enhancement network, the illumination brightness conditions of the soybean plant images are adjusted, and the image noise and color distortion are removed, so as to improve the accuracy of soybean plant feature detection and matching under low illumination and reduce the feature mismatch. The spatial point cloud information and camera pose are obtained by combining the internal and external parameters of the camera. The problem of inaccurate estimation of spatial point cloud shape and inaccurate camera pose caused by illumination constraints is solved. Finally, the SFM algorithm and the PMVS (the patch-based MVS algorithm) [30] algorithm are used to reconstruct the three-dimensional soybean plant, so as to realize the perception of soybean plant growth environment in low-illumination working environment.

In this paper on low-illumination soybean plant reconstruction and trait perception, the following main contributions are provided:

- (1) The soybean plant image under low illumination is adjusted by the EnlightenGAN image enhancement network to remove the image noise and color distortion. The enhanced soybean plant image is closer to the actual illumination brightness, and the color is real. It highlights the contour structure, feature points, and boundary information of the soybean plants in the image, which is conducive to the subsequent image analysis and processing such as feature point extraction and matching.
- (2) The soybean plant image after the illumination brightness enhancement can detect a large number of fine soybean plant feature points, including more abundant and detailed plant information, which solves the problem of the detection of the soybean plant feature points in low illumination environment being less and the corresponding relationship between soybean plants under different perspectives being difficult to establish and the color of the reconstructed point cloud model being singular. A large number of fine soybean plant feature points are matched to optimize the reconstructed soybean plant model.
- (3) A large number of fine soybean plant feature points can reduce the mismatch of soybean plant feature points and construct a point cloud model close to the actual soybean plant. The recovery of soybean plant phenotypic structure is very excellent, and the texture is rich and colorful. Detailed soybean plant phenotypic analysis is conducive to evaluating soybean plant morphology and traits and accurately sensing soybean plant growth information.

2. Three Dimensional Reconstruction of Soybean Plants under Low Illumination

During the operation of farmland, the complex production environment of a soybean field, the diversity of soybean plants, and how to obtain accurate information on those soybean plants have caused troubles for the operation of agricultural machinery and

equipment. Agricultural machinery and equipment can easily cause irreparable damage to soybean plants during the collection of soybean growth information. In addition, the complex and changeable field environment and the diversity of soybean plants make it impossible for agricultural machinery and equipment to monitor the growth status of soybean crops in real time, which increases the difficulty of collecting information on soybean plants. By applying three-dimensional reconstruction technology to the perception process of agricultural machinery and equipment on soybean plants, a three-dimensional model close to the actual soybean plants was constructed to generate fine soybean plant phenotypes, to achieve non-contact collection of more comprehensive and specific accurate information of soybean plants, to quickly and efficiently evaluate the growth status of soybean plants, and to provide accurate information for agricultural machinery and equipment to carry out field soybean plant operations. In the reconstruction of a soybean plant model under low illumination, as shown in Figure 1, through the EnlightenGAN image enhancement network for the collected multi-view samples of soybean plants under low illumination, the brightness-enhanced soybean plant image is obtained by illumination adjustment. The SIFT (scale-invariant feature transform) [31] algorithm is used for image feature detection. The feature points are different from other ordinary pixels on the image. It contains more key information needed for three-dimensional reconstruction. The quality of feature point detection directly determines the accuracy of the three-dimensional reconstruction model. The effective and low error rate feature points are used to match the feature points of images from different perspectives. According to the paired matching feature points, the SFM algorithm is used to determine the three-dimensional structure of soybean plants, and the sparse point cloud of soybean plants [32] is generated. The dense three-dimensional point cloud of soybean plants is restored by the patch-based PMVS algorithm, and a three-dimensional model close to the actual soybean plants is reconstructed.



Figure 1. Reconstruction diagram of soybean plant model under low illumination.

2.1. Soybean Plant Image Acquisition

The definition of low illumination in this paper is that the illumination of the camera when shooting soybeans makes the output video signal level lower than the specified brightness value of the soybean image, so that the light intensity of the soybean is relatively low and the brightness is relatively dark. In this light condition, the camera can vaguely see the available image of the soybean contour under the condition of a certain degree of darkness, and the illumination is used as the measurement unit of the light brightness. If the brightness value of the soybean image is lower than the minimum illumination of the camera, the amplitude of the output video signal will not reach the specified brightness value of the soybean image. The collected soybean image is dark and it is difficult to distinguish the contour level of the soybean. Even if the method of this paper is used to enhance the brightness of the image to reconstruct the soybean plant, the soybean information is inaccurate and partially missing, so that the three-dimensional model of the soybean plant cannot be reconstructed.

In this paper, the three-dimensional soybean plant model is reconstructed. When collecting the required soybean plant image data set, it is recommended to take the soybean plant grown for about two months as the shooting object. Because the soybean plant structure at this stage is obvious and the contour is clear, it is convenient to compare and analyze before and after the experimental treatment. Moreover, when shooting soybean plants, the three-dimensional model of soybean plants reconstructed by selecting farmland

scenes with small plant density and dense plant scenes to evaluate the growth status of the current plants will be affected by adjacent plants. In order to meet the actual application environment, the soybean shooting process was selected in the farmland environment at night, and the environment brightness was set by controlling the input current of the adjustable LED lamp to simulate the soybean growth environment under low illumination. Through the Intel Realsense D435i camera, the multi-view shooting is carried out with the center of the soybean plant to be reconstructed under low illumination. The low-illumination soybean image is collected around the soybean plant in an orderly manner. During the collection process, the soybean is collected as far as possible from the near and far distance perspectives. In this way, a large number of low-illumination soybean plant images collected contain different height information, which is conducive to the accurate reconstruction of soybean plants. When shooting soybean plants, the camera captures an image every 10 degrees per revolution and retains more of the same soybean plant structure in the adjacent image, which is not only beneficial to completing the image stitching of soybean plants, but also makes the soybean plant reconstruction rich in details and reduces the time spent on image matching. A total of 826 multi-view images of soybean plants under low illumination were collected in the experiment. The number of point clouds obtained from each angle should not be less than 10. If the number of point clouds is too small, the images of adjacent frames cannot be matched. The experiment obtained 9166 point clouds of soybean plants. In addition, the experiment carried out data collection under a normal lighting environment, and 796 soybean images were collected. About 3200 point clouds could be obtained from each angle. There were 2,623,616 soybean plant point clouds collected under the normal lighting environment. As shown in Figure 2, some images under normal light collected in the experiment can clearly observe the fine knot structure and rich texture of the soybean in the image of the soybean plant under normal light as shown below, while the light brightness of the soybean plant image under low light is very low and fuzzy, which makes it difficult to observe the shape and character of the soybean plant, and the captured value information of the soybean plant is very limited. It is not easy to reconstruct a 3D model close to the real soybean plant, which greatly improves the difficulty of environmental perception of the current growth state of soybean plants.

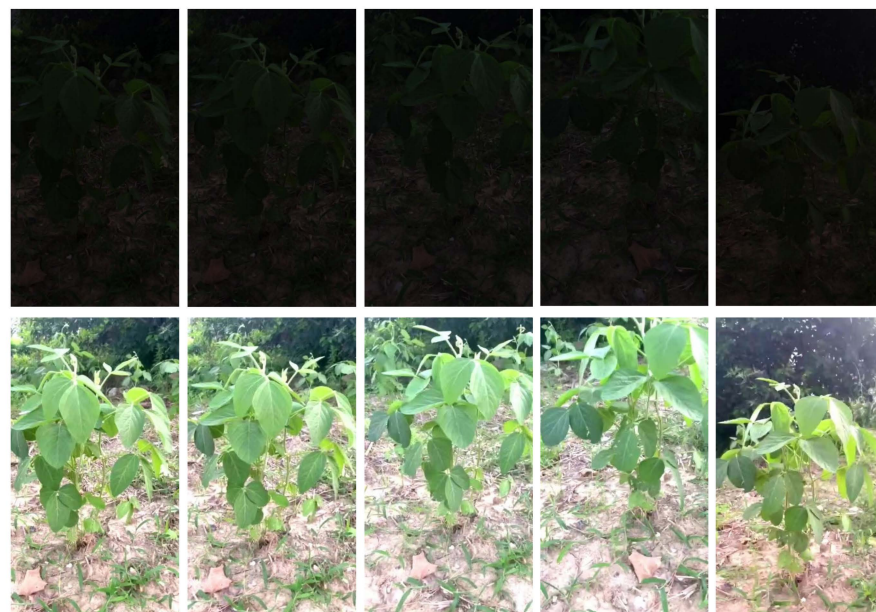


Figure 2. Soybean plant images collected in the experiment.

2.2. Low-Illumination Soybean Plant Image Enhancement

When agricultural machinery and equipment are working at night, the collected images of soybean plants under low illumination have the problems of detail loss and

insufficient contrast and low-illumination conditions, which greatly affect the visual quality of the images. In order to improve the image quality as much as possible, this paper uses the low-illumination image enhancement network, EnlightenGAN, based on deep learning. Its main function is to improve the brightness of low-illumination soybean plant images, and at the same time retain the effective information of soybean plants to the greatest extent in the enhancement process. The high-brightness pixels will not be overbrightened, and the image noise will be suppressed, thus solving the problem of insufficient illumination conditions. The enhanced image is more prominent in the soybean plant image structure characteristics, which is conducive to the soybean plant image feature detection and image matching and further enhances the effect of three-dimensional reconstruction based on multi-view.

The EnlightenGAN image enhancement network uses an attention-guided U-Net as a generator to guide soybean plant information through a global and local dual discriminator, using self-feature retention losses to guide the training process, as shown in Figure 3. The generator network is composed of a feature extraction module, an information reconstruction module, and a brightness adaptive module. The feature extraction module mainly extracts image feature information. The information reconstruction module recovers the image information from the extracted image feature map through deconvolution operation. The brightness adaptive module adjusts the illumination brightness freely, so that the enhanced image will not have overexposure or underexposure. In order to improve the global illumination while adaptively enhancing the local area illumination, the global-local structure dual discriminator uses PatchGAN [33] to identify the normal-illumination image and the enhanced image. The judgment information of the two discriminators will be fed back to the generator to continuously adjust the image enhancement effect, so that the enhanced image and the normal-illumination image cannot be distinguished by the two discriminators, thus completing the adaptive enhancement of the image. The local discriminator randomly cuts five local blocks from the enhanced soybean plant image and the normal-illumination soybean plant image and learns to distinguish them from the normal-illumination image or the enhanced image. The global-local structure can make the local blocks of the enhanced image close to the normal-illumination image, which is the key to avoiding local overexposure or underexposure. The global discriminator uses the relativistic discriminator structure to estimate the probability that the normal-illumination soybean plant image is more realistic than the enhanced soybean plant image, so that the generator synthesizes the enhanced soybean plant image more realistic than the normal-illumination soybean plant image. The generator normalizes the illumination channel of the input RGB image, uses the difference between the elements to generate the self-regularized attention map, adjusts the size of the attention map to extract the multi-level features of different depth layers, retains the rich texture information of the image, and uses the multi-scale context information to synthesize high-quality enhanced images, combined with the discriminator feedback identification information. So that the output image dark area will not be overexposed or underexposed, it effectively removes the noise hidden in the dark area, color distortion and other degradation problems, and adjusts the appropriate lighting conditions to maintain the texture and structure of soybean plants.

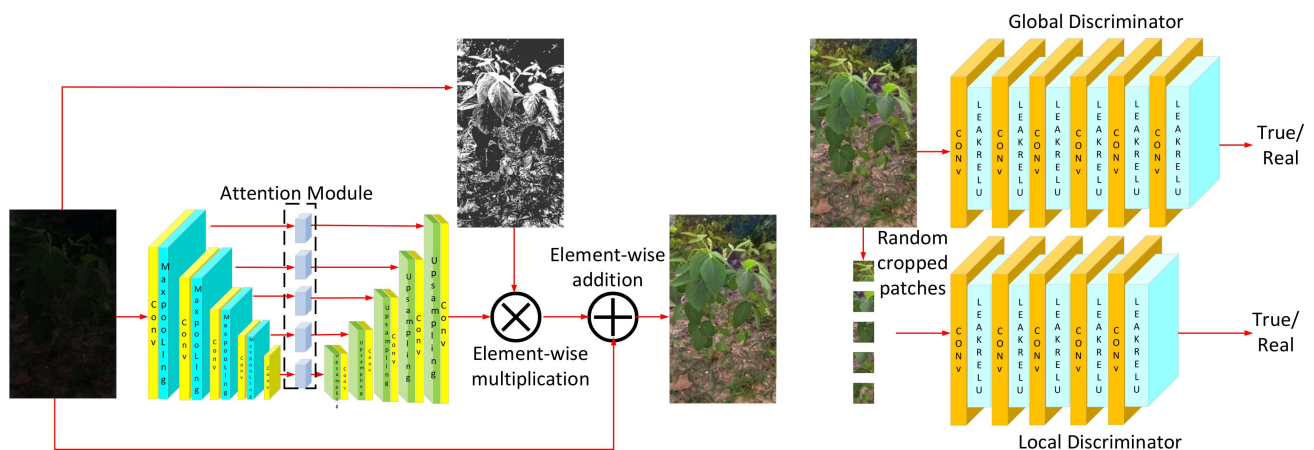


Figure 3. Soybean plant image enhancement model.

2.3. Point Cloud Reconstruction of Soybean Plant

2.3.1. Feature Detection and Matching

With image feature detection and matching as a key part of the three-dimensional reconstruction, the establishment of the corresponding relationship between soybean plant images obtained from different observation angles and the corresponding relationship between images obtained from different perspectives is the key information to generating three-dimensional reconstruction of subsequent point cloud reconstruction. For the soybean plant image feature detection and matching, as shown in Figure 4: Firstly, building a Gaussian differential pyramid for the input enhanced soybean plant images achieves the multi-scale space construction of soybean plant images. Secondly, the key points of the soybean plant are determined by the detection of extreme points in the scale space of the soybean plant image, and the main direction of feature points is established to generate the feature description vector of the soybean plant and complete the feature matching task of the soybean plant.

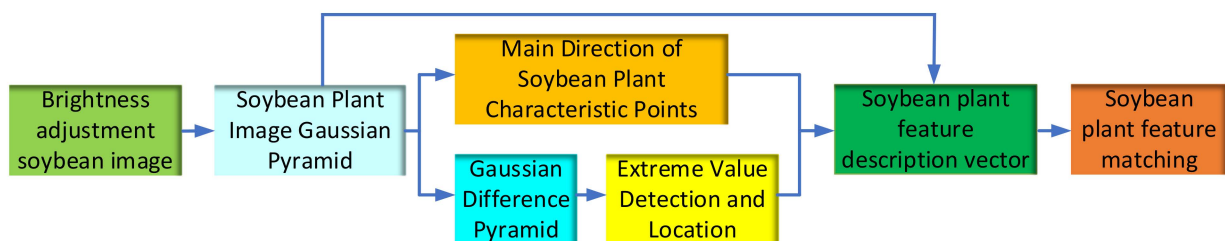


Figure 4. Detection and matching of soybean plant characteristics.

Gaussian difference pyramid is the premise of detecting the extreme points of soybean plant image in the later stage. As shown in Figure 5, the Gaussian difference pyramid of the soybean plant image is obtained by subtracting the adjacent layers in each group of image sequences in the Gaussian pyramid composed of multiple groups of soybean plant image sequences. Each group of soybean plant image sequences in the Gaussian pyramid is calculated by convolution of the basic image $I(x, y)$ in the group and the Gaussian function $G(x, y, \sigma)$ that changes the scale factor σ multiple times. The adjacent layers in the same group of image sequences are subtracted to form the Gaussian difference pyramid convolution $D(x, y, k\sigma)$, thus constructing a multi-scale space where $k\sigma$ and σ is the scale factor of different layers. $G(x, y, \sigma)$ denotes a Gaussian function with a scaling factor. Formulas (1)–(3) are:

$$D(x, y, k\sigma) = [G(x, y, k\sigma) - G(x, y, \sigma)] \otimes I(x, y) \quad (1)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

$$\sigma(o, r) = \sigma_0 2^{o+\frac{r}{n}}, o \in [0, 1, \dots, O-1]; r \in [0, 1, \dots, n+2] \quad (3)$$

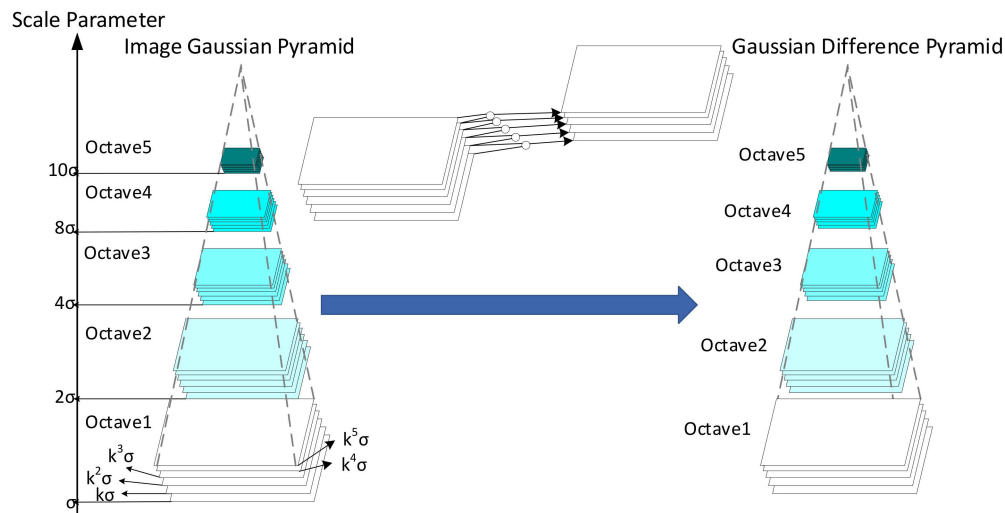


Figure 5. Construction of Gaussian difference pyramid of soybean plant image.

$\sigma(o, r)$ represents the Gaussian blur coefficient of the corresponding soybean plant image: that is, the scale factor of the corresponding layer, where o is the index number of each image sequence group of the Gaussian pyramid; r is the scale image layer index number in a set of image sequences; and σ_0 is the Gaussian blur initial value.

The extreme point detection of the soybean plant scale space is performed by comparing the $D(x, y, k\sigma)$ value of 26 adjacent points between the adjacent two layers of images in the same group of the points to be detected in the Gaussian difference pyramid; to ensure that the $D(x, y, k\sigma)$ value of the detection point is the maximum or minimum value of its adjacent points, the detection point is determined to be a key point of the image at this scale, and the feature information coordinates (x, y) and scale $L(x, y)$ of the point are recorded. Through histogram statistics, the gradient amplitude and direction corresponding to the pixels in the neighborhood of the key points of soybean plants are calculated. The cumulative peak of the gradient amplitude is the main direction of the key points, and the corresponding feature point descriptors are generated to make them not change with various changes, to improve the probability of the correct matching of feature points. After screening and normalization, the final soybean plant feature description vector is obtained, in which the gradient amplitude m and direction θ calculation Formulas (4) and (5) are:

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \quad (4)$$

$$\theta(x, y) = \tan^{-1} \left[\frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)} \right] \quad (5)$$

After the feature description vectors of two soybean plant images are generated, a feature description vector V in one image is taken, and the first two feature description vectors V_1 and V_2 with the closest Euclidean distance in the other image are found, and the distance is $Dist(V, V_1) < Dist(V, V_2)$. If the ratio of the nearest distance to the second nearest distance in these two feature points is less than the set proportional threshold M ,

the nearest distance feature description vector is matched with the feature description vector. The calculation Formulas (6) and (7) are:

$$Dist(V, V_1) = \sqrt{\sum_{i=1}^n (v_i - v_{1i})^2}, Dist(V, V_2) = \sqrt{\sum_{i=1}^n (v_i - v_{2i})^2} \quad (6)$$

$$\frac{Dist(V, V_1)}{Dist(V, V_2)} < M \quad (7)$$

A large number of two soybean plant images with arbitrary scale, rotation, and brightness changes are matched. The optimal proportion threshold is set between 0.4 and 0.6. In the process of soybean plant matching, the proportion threshold is set to 0.5. For the matching with high accuracy requirements, the proportion threshold is 0.4; when the number of matching points requires more matching, the ratio threshold is 0.6.

2.3.2. Space Point Cloud Reconstruction

The sparse point cloud of soybean plants can reflect the general morphology and traits of current soybean plants. After observing the surrounding soybean plants, the three-dimensional appearance of the soybean plants is perceived. The point cloud is used to represent the three-dimensional structure of the soybean plants. The camera pose is obtained by the motion recovery structure. A large number of multi-view soybean plant images are used to obtain the sparse point clouds of soybean plants. The multi-view dense matching method based on patch is used to generate the dense point cloud model of soybean plants.

Because the original EXIF (exchangeable image file format) information of the collected images will be lost in the process of image enhancement, it is difficult to determine the camera pose, which seriously affects the effect of reconstructing the three-dimensional model of soybean plants. In this paper, the SFM algorithm is used to restore the three-dimensional point cloud model from multi-view soybean plant images, as shown in Figure 6. Firstly, the EXIF information of each soybean plant image is extracted, which contains the attribute information and shooting data of each image, so as to obtain the internal reference information of the camera. Secondly, the feature detection and matching of the soybean plant image adjusted by illumination are carried out to obtain the feature point pairs. Combined with the epipolar constraint between the two soybean plant images, the matching pairs are optimized by the algorithm, and the singular value decomposition of the essential matrix is carried out to solve the camera pose and obtain the external reference information. In this process, the distance between the source point cloud set $P = \{p_1, p_2, \dots, p_n\}$ and the target point cloud set $Q = \{q_1, q_2, \dots, q_n\}$ is minimized by finding a spatial optimal transformation matrix composed of a rotation matrix R and a translation matrix t . The above matching process is iterated continuously to form an image trajectory around the soybean plant. The calculation Formula (8) is:

$$E(R, t) = \frac{1}{n} \sum_{i=1}^n \|q_i - (Rp_i + t)\|^2 \quad (8)$$

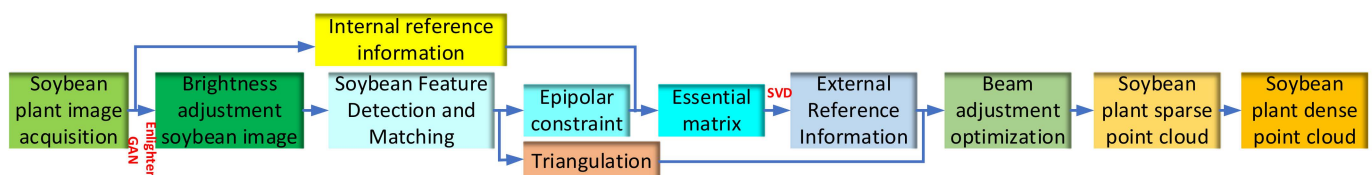


Figure 6. Point cloud reconstruction of soybean plant.

The angle between the feature points of the same soybean plant is observed from two perspectives, and the position relationship of the point is determined. The three-dimensional coordinates of the feature points of the soybean plant in the world coordinate system are solved. The camera pose and the point cloud of the soybean plant are optimized by bundle adjustment in turn to reduce the difference between the projection and reprojection of the real three-dimensional space points on the image plane. After the bundle adjustment optimization, the accurate camera pose and the three-dimensional coordinates of the soybean plant point cloud are obtained, and the sparse point cloud model of the soybean plant is generated.

Because the sparse point cloud of the soybean plant is different from the real soybean plant in appearance, it cannot fully express the real shape and character of the soybean plant. Therefore, it is necessary to make the sparse point cloud of the soybean plant denser, so that the reconstructed soybean plant model is closer to the actual soybean plant. Through the relevant information provided by the sparse point cloud, the patch-based PMVS algorithm is used to restore the dense point cloud of soybean plants, and the point cloud model of the soybean plants is generated accurately and efficiently. According to the spatial points in the sparse point cloud of soybean plants, the surface slices of the soybean plant model are generated in order of the distance from the point to the camera optical center from near to far, and the neighborhood image set that conforms to its certain constraints is set for each surface slice. The existing surface slices are iterated continuously to generate more slices, and the individual or wrong surface slices are eliminated to generate a dense point cloud model of soybean plants closer to the real soybean plant morphology and traits.

3. Experimental Analysis of Three-Dimensional Reconstruction of Soybean Plant

3.1. Experimental Environment

This article is an experiment using the Windows10 system. The processor uses Intel (R) Core (TM) i5-10600KF, graphics card NVIDIA GeForce RTX 3060, hard disk 1 TB, and memory 16 GB. Based on CUDA11.1 and Cudnn11.1, Tensorflow1.8.0 and Pytorch1.6.0 frameworks are selected in the Python3.8 compilation environment for experimental model training and testing in the Pycharm2018 community version.

3.2. Evaluating Indicator

3.2.1. Image Enhancement Evaluation Index

In this paper, the image enhancement uses the usual quantitative indicators peak signal to noise ratio (PSNR) and structural similarity (SSIM) as the evaluation criteria for soybean plant image enhancement. The experiment compares the average PSNR and SSIM of the test set. The higher the value, the better the model is at the light adjustment and the soybean plant detail recovery enhancement effect, so as to select the better enhanced image to reconstruct the soybean plant model. PSNR evaluates the effect of the image enhancement by judging the pixel difference between the enhanced soybean plant image and the normal-illumination image, where $\max_1$ represents the maximum pixel value of the image, MSE represents the mean square error value of the image pixel, and x and y represent the two soybean plant images before and after enhancement. Formulas (9) and (10) are as follows:

$$PSNR = 10 \times \log_{10} \left(\frac{\max_1^2}{MSE} \right) \quad (9)$$

$$MSE(x, y) = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n (x(i, j) - y(i, j))^2 \quad (10)$$

SSIM is used to evaluate the degree of detail similarity of soybean plant by judging the structural differences between images. The image similarity is mainly measured from three aspects: brightness $I(x, y)$, contrast $c(x, y)$, and structure $s(x, y)$, where μ_x and μ_y represent the mean values of image x and y , respectively. δ_x and δ_y represent the variance of image

x and y , respectively. δ_{xy} represents the covariance of image x and y , C_1 , C_2 , and C_3 are constants. The Formulas (11)–(14) are as follows:

$$SSIM(x, y) = l(x, y) \times c(x, y) \times s(x, y) \quad (11)$$

$$l(x, y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_2} \quad (12)$$

$$c(x, y) = \frac{2\delta_x\delta_y + C_2}{\delta_x^2 + \delta_y^2 + C_2} \quad (13)$$

$$s(x, y) = \frac{\delta_{xy} + C_3}{\delta_x\delta_y + C_3} \quad (14)$$

3.2.2. Feature Point Detection Evaluation Index

In this paper, repeatability is used as the standard to judge the advantages and disadvantages of feature point detection methods, and the matching time of feature points is used as the evaluation criterion of feature matching efficiency. The evaluation criterion was proposed by KMikolajczyk et al. [34] after comparing different local feature descriptors. Considering the different detection algorithms and the different detection shapes of feature regions, the evaluation criterion is optimized. Formula (15) is as follows:

$$R = \frac{N}{\min(N_a, N_b)}, (N_a \in I_A, N_b \in I_B) \quad (15)$$

where R represents the repeatability rate, N represents the number of repeated points, I_A and I_B represent the graph A and graph B to be matched in the same scene, respectively, and N_a and N_b represent the number of feature points detected in I_A and I_B , respectively. Considering that there must be a non-overlapping range between the two graphs, the coordinates of the feature points in I_A are mapped to the I_B coordinate system through the homography matrix, and the coordinates beyond the range of the I_B coordinate system are removed. The number of N_a is updated, and then, the number of N_b is updated by doing the same operation on I_B .

Since the homography matrix mapping process is mainly used to project the coordinates of one of the image feature points onto another image coordinate system through this matrix, the splicing of two images is realized. However, in the actual feature point detection and matching, it is not perfect, and there will be errors and mismatches. Therefore, the minority obeys the majority to retain the optimal data and reduce the error of the homography matrix mapping process. The coordinates of the N_a feature points updated in I_A are calculated in the I_B coordinate system by the homography matrix H mapping, and the Euclidean distance is solved with the updated N_b feature point coordinates to determine whether the distance is less than the set threshold ε . If it is less than the set threshold, it is established as a repetition point and counted in N . The iteration to obtain the homography matrix H corresponding to the maximum N is the mapping process that is least affected. Moreover, the optimized repeatability rate limits N , and it is required to set ε to 1.5 and the overlap error between I_A and I_B is less than 0.2, where a and b represent the feature points of I_A and I_B , respectively, and I_A and I_B represent the image after the feature points out of the range are eliminated. Formula (16) is as follows:

$$\|a \cdot H - b\| < \varepsilon, (a \in I_{A'}, b \in I_{B'}) \quad (16)$$

3.3. Evaluation of Three-Dimensional Reconstruction Experiment of Soybean Plant

3.3.1. Soybean Plant Image Enhancement Evaluation

The enhanced soybean plant images are evaluated using multi-view soybean plant images collected at low illumination. Experiments compare different classical image enhancement networks for a test set of soybean plants and test the image enhancement

effect of different image enhancement networks on soybean plants at low illumination. As shown in Figure 7, soybean plant images enhanced by the RetinexNet algorithm suffer from overexposure, color distortion, and local area blurring. The overexposure of the KinD++ algorithm [35] is mitigated, but the colors are not realistic. The sharpness of the leaves of the soybean plants is high and contains visible noise. The LIME algorithm alleviates the overexposure and color distortion to some extent, but the brightness is not improved enough and there is texture distortion. The MBLEN algorithm has better color restoration, but the local area of the soybean plant is dark and deviates from a natural light image. The color and noise of the soybean plant images are well processed by the SCI algorithm [36], but the brightness is dimmer after enhancement. The EnlightenGAN algorithm enhances the soybean image with a light brightness closer to the natural light brightness to recover better and more natural color for soybean details. As shown in Table 1, different algorithms are used to enhance the contrast of the soybean plants. The high SSIM of the EnlightenGAN algorithm indicates that the structure and texture details of soybean plants are well recovered at low illumination. Although its PSNR is lower than that of the KinD++ algorithm, the enhanced illumination brightness of the KinD++ algorithm is more prominent, but the actual illumination enhancement is improved by the EnlightenGAN algorithm.

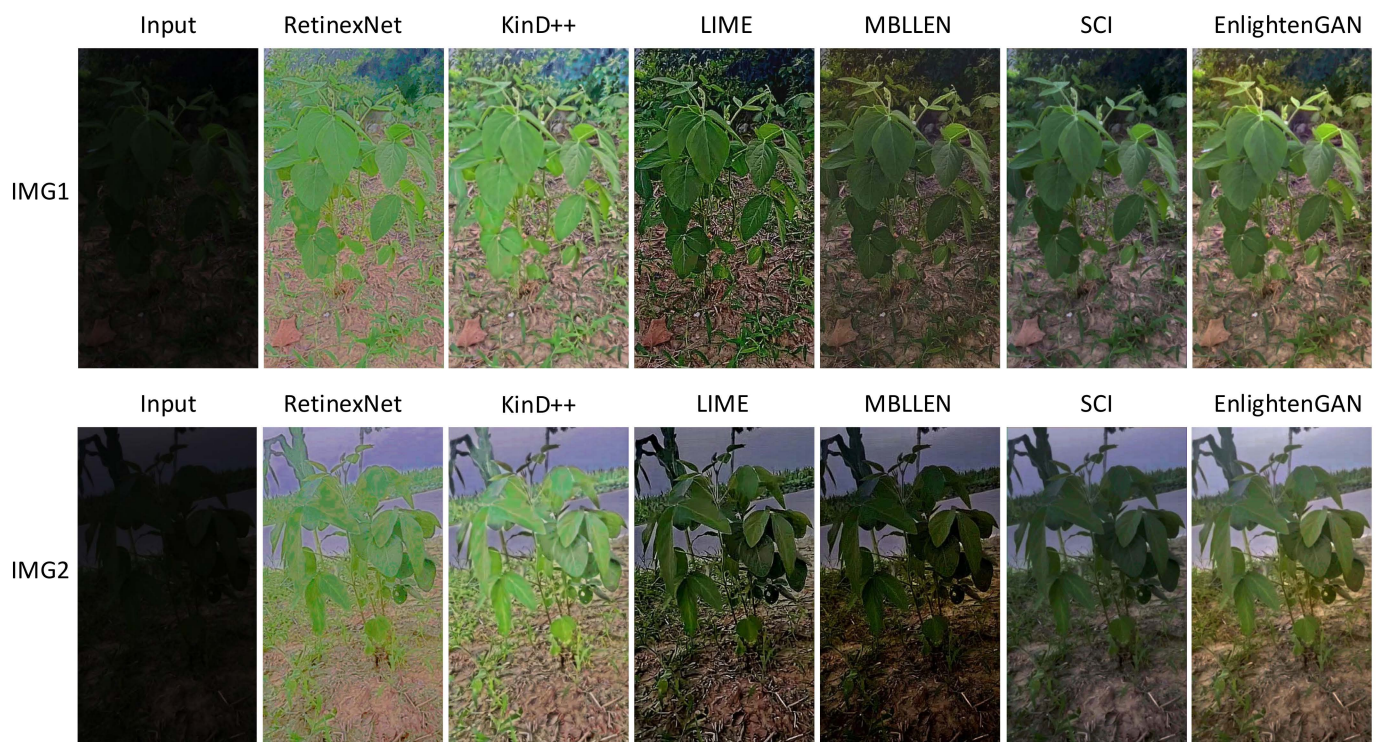


Figure 7. Comparison of soybean plant image enhancement effect.

Table 1. Comparison results of different algorithms.

Algorithm	PSNR	SSIM
Input	−6.82	0.14
RetinexNet	18.99	0.84
KinD++	19.40	0.88
LIME	11.17	0.39
MBLEN	10.65	0.63
SCI	10.83	0.81
EnlightenGAN	17.37	0.92

The soybean plant image with natural light environment and rich detail information is an important data source for reconstructing the soybean plant model. Therefore, this paper selects the EnlightenGAN enhancement network to adjust the lighting conditions of the low-illumination soybean plant image, to effectively remove the noise and color distortion hidden in the dark area, and to generate the soybean plant image with suitable illumination brightness and rich information. The soybean plant contour structure, feature points, and boundary information in the image are more clearly highlighted, which is more conducive to the subsequent image analysis and processing such as feature point extraction and matching. The enhanced soybean plant image can perceive accurate soybean plant growth information. The accuracy of feature point detection and matching of soybean plants was improved to optimize the reconstructed soybean plant model and make it closer to the morphology and traits of real soybean plants.

3.3.2. Evaluation of Soybean Plant Model Reconstruction

Aiming at the three-dimensional model of soybean plants under different illumination conditions, this study obtains a set of soybean plant images after adjusting illumination through the soybean plant image enhancement network and performs image feature detection and matching with the collected soybean plants under low illumination to compare the feature detection performance under different illumination environments.

By comparing the detection and matching of feature points in four groups of two adjacent soybean plant images before and after light environment adjustment and under a normal-light environment, it shows the improvement of feature point detection and matching after light adjustment of soybean plant images and evaluates the impact of the light adjustment of soybean plant images on the reconstruction of soybean plant models. As shown in Figure 8, the detection and matching of feature points on adjacent frame images of soybean plant under low illumination are carried out. A very small number of feature points in the four groups of soybean plant images under low illumination are detected. The feature points of the four adjacent plant images are matched. Due to the small number of feature points detected in the soybean plant images under low illumination and the differences in the feature points detected from different perspectives, the number of successful matches of the feature points of the four adjacent soybean plant images is limited, which can easily cause the mismatch of soybean plant features. It increases the difficulty of establishing the correspondence between soybean plants from different perspectives, which is affected by light constraints. It is easy to produce incorrect spatial point cloud estimation and inaccurate camera trajectory, and different image features cannot be matched, which greatly affects the reconstruction accuracy of the three-dimensional model of the soybean plant. As shown in Figure 9, it shows the detection and matching of feature points on adjacent frame images of soybean plant under a normal-light environment. Compared with the feature detection and matching results shown in Figure 8, we can clearly see that more soybean feature points can be detected under a normal-light environment, which is related to whether the soybean model reconstruction is complete, which also leads us to match four groups of soybean plant images under a normal-light environment. More successful feature matching can be obtained, which helps to improve the precision of our model reconstruction.

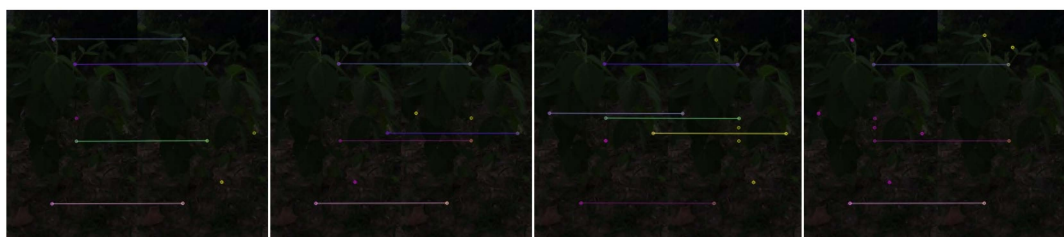


Figure 8. Detection and matching results of feature points in adjacent frames of soybean plants under low illumination.

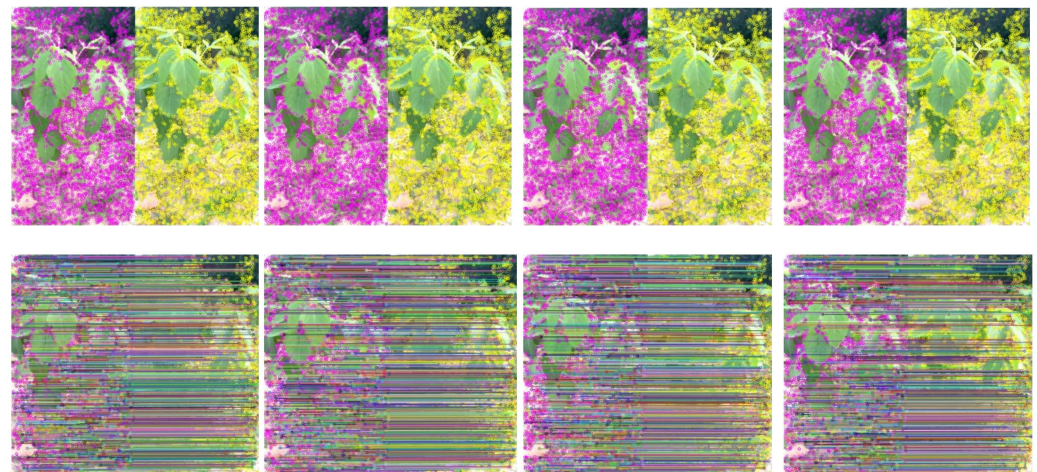


Figure 9. Detection and matching results of feature points in adjacent frames of soybean plants under normal light.

Four groups of adjacent soybean plant images collected at low illumination are adjusted by the EnlightenGAN enhancement network, which effectively removed the image noise at low illumination to improve the image quality and recover more soybean plant image details. As shown in Figure 10, the adjacent frame images of soybean plants with improved illumination conditions are generated and the feature points of the soybean plants are detected. It is clear that the number of feature points detected in the soybean images after adjusting the illumination environment of the four groups is greatly increased and its feature performance is better than that of the soybean images without adjusting the illumination. The feature point pair matching was performed on the detected soybean plant image. Neighboring images from different perspectives increase the number of feature pairs successfully matched compared to images without illumination adjustment, and the accuracy of image matching is also improved. Compared to the real features of soybean plants extracted at normal illumination, the real features of soybean plants extracted at low illumination are very limited, and the images of soybean plants without illumination adjustment are easily masked by false features, resulting in the false matching of soybean plant features. After the adjustment of illumination conditions, the soybean plant image can extract more real features and capture more abundant soybean plant information, which provides convenience for the establishment of the corresponding relationship between different perspective images of soybean plants, and also provides accurate information for the point cloud reconstruction of soybean plants in the later stage, so that the reconstructed soybean plant model is closer to the morphology and traits of real soybean plants.

By testing the feature detection and matching of the collected four groups of adjacent matching images and the four groups of adjacent matching images after the illumination environment is adjusted, the number of feature points detected by adjacent images, the number of image matching pairs, the repeatability rate, and the feature point matching time are used to illustrate the influence of the illumination environment on the image feature points. As shown in Table 2, Figure A and Figure B in the table represent the adjacent frame images to be matched. It is obviously observed that the performance of the soybean plant image feature point detection after the light adjustment has been greatly improved. The number of soybean plant feature points detected has increased, which is close to the soybean plant feature points detected under the normal light environment, so that the missing of feature detection information can be reduced compared with the image before the light adjustment. Obtaining more precise soybean plant information and establishing more accurate correspondence between images, while the repeatability of the feature point matching has been improved to a level close to the repeatability of the feature point matching under normal lighting environment, indicates that the probability of correct image matching has been improved while reducing feature point mismatch. Due to the

adjustment of the light environment, when detecting a large number of feature points of soybean plants, the overhead of certain computing resources is indispensable, and the matching of a large number of feature points of soybean plants requires more time to calculate, and in the process of image processing, inevitably, there will be a certain amount of information redundancy, resulting in the extension of processing image time, but the increase of feature matching time can be obtained. Both the number of feature points and the number of image matching pairs increase significantly, capturing rich and accurate soybean plant information and improving the accuracy of the reconstructed soybean point cloud.

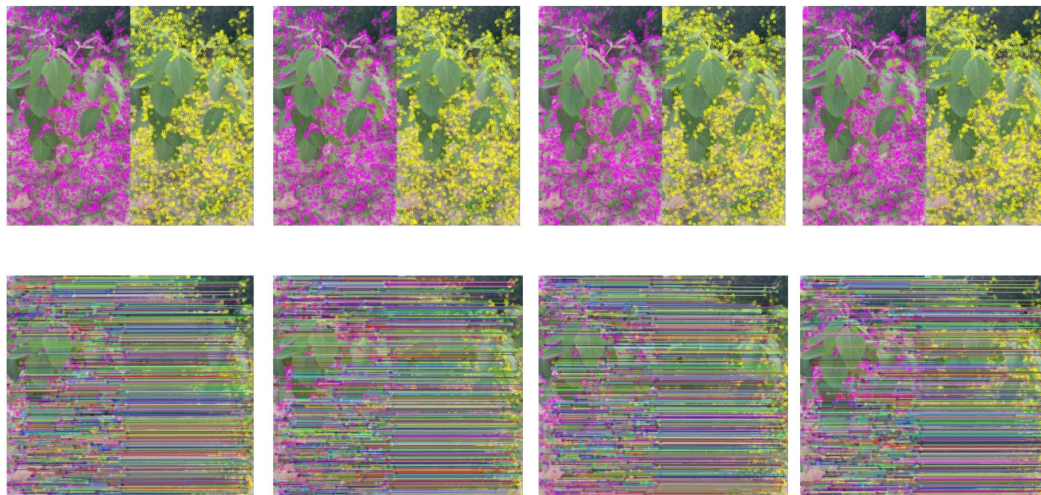


Figure 10. Detection and matching results of feature points in adjacent frames of soybean plants after light adjustment.

Table 2. Feature detection and matching of four adjacent soybean plant images.

Light Brightness	Figure A Average Number of Feature Points (N_a)	Figure B Average Number of Feature Points (N_b)	Average Number of Image Matching Pairs (N)	Repeatability (R)	Average Time of Feature Point Matching (Unit: s)
Unadjusted	10	11	5	0.5	0.0011
Normal	3227	3307	1836	0.5689	0.1965
After adjustment	2245	2281	1211	0.5394	0.1267

4. Discussion

In this study, we performed three-dimensional reconstruction of a soybean plant environment by adjusting the illumination conditions of soybean plant images and compared the impact of the illumination conditions on the reconstruction effect of the soybean plant model. It showed that the adjustment of the appropriate illumination environment brings the reconstructed soybean plant model closer to the real soybean plant, and the reconstructed soybean plant phenotype has the detailed soybean plant current growth morphology and traits. In Figure 11, it shows the sparse point cloud model reconstructed from the same soybean plant under low illumination and the dense point cloud model of its corresponding view, in which a large number of different color dots constitute the structural characteristics of soybean plants. The sparse point cloud of a soybean plant at low illumination is observed from the sparse point cloud of a soybean plant at low illumination above the image. The generated sparse point clouds of soybean plants contain fewer soybean point clouds. The soybean plant information with limited illumination constraints produces incorrect spatial point cloud estimation and inaccurate camera trajectory. The correct rate of matching between different image features is very low. After surface slicing, a dense point cloud of soybean plants in low illumination is constructed below the image,

where it is difficult to observe the general outline of soybean plants. It was found that because the soybean plant image cannot obtain the texture information of the leaves under low illumination, the reconstructed dense point cloud model of the soybean plant is more unable to observe the morphology and traits of the soybean plant, and it is difficult to evaluate the current growth status of the soybean plant.

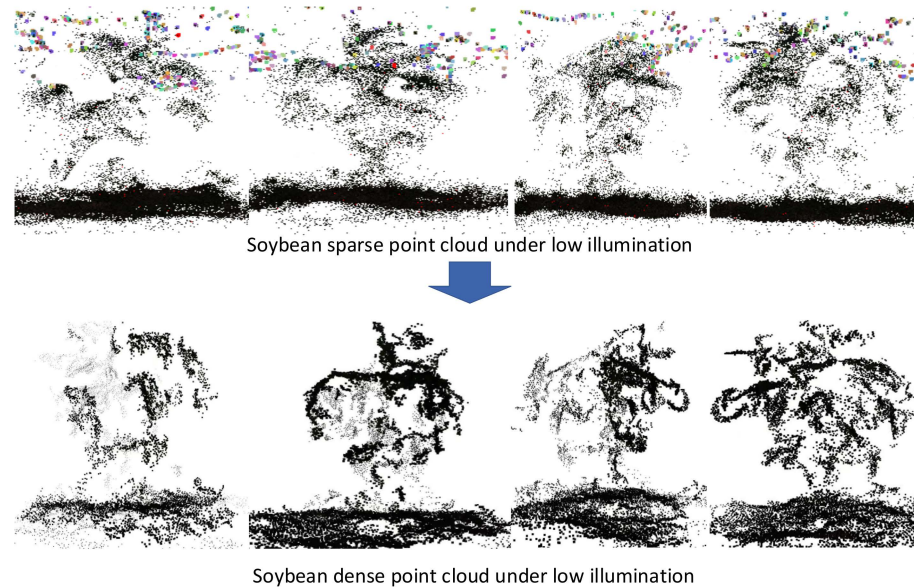


Figure 11. Reconstruction of soybean plant model under low illumination.

The experiment conducted the reconstruction of the sparse point cloud model of the same soybean plant and the dense point cloud model of its corresponding view under normal light conditions, as shown in Figure 12. The soybean sparse point cloud model reconstructed under normal light at the top of the figure can be clearly observed. The rebuilt soybean sparse point cloud model under light can easily see the general outline and growth structure of soybean plants. The model with the dense point cloud of the soybean plant under normal light in the lower part of the figure simulates a model similar to the actual soybean plant in appearance. Additionally, compared with the soybean plant model reconstructed under low illumination, it is obvious that the structure and color of the soybean appearances are diverse, the rich texture surface is also clearly visible, and the characteristics of the soybean plant leaves can be observed in detail.

The illumination environment of the collected soybean plant images is adjusted to generate a sparse point cloud based on the paired matched feature points of the soybean plant, and the dense three-dimensional point cloud of the soybean plant is recovered by surface slicing, as shown in Figure 13, where the sparse point cloud model reconstructed from the same soybean plant after enhancement and the dense point cloud model from the corresponding perspective are shown. For the sparse point cloud model reconstructed from the multi-view image, due to the increase in the number of feature points that are adjusted for the detection of light brightness and correctly matched, the light-adjusted soybean sparse point cloud reconstructed from the top of the figure is almost the same as the sparse point cloud of soybean plants under normal light, and the contour of the soybean plants can also be observed, and the general characteristics of soybean plants can be seen. The model of the soybean plants with dense point clouds at the bottom of the figure is, in appearance, also very close to the actual soybean plant. In addition, the reconstructed soybean plant model is similar to the soybean plant reconstructed under normal lighting conditions in appearance. It also has a complex and detailed structure, various colors, and rich texture surface. However, it is difficult to extract information from the image under low illumination. The acquired multi-view soybean plant image is subject to light adjustment, which can reduce the noise information of the image to a certain

extent. The contour structure, feature points, and boundary information of the soybean plants in the image are more prominent. The distinct three-dimensional model of soybean plant structure information reconstruction makes the differences between the reconstructed soybean plant model and the model reconstructed under normal light small and realizes the perception of soybean plant growth in a low-light environment.

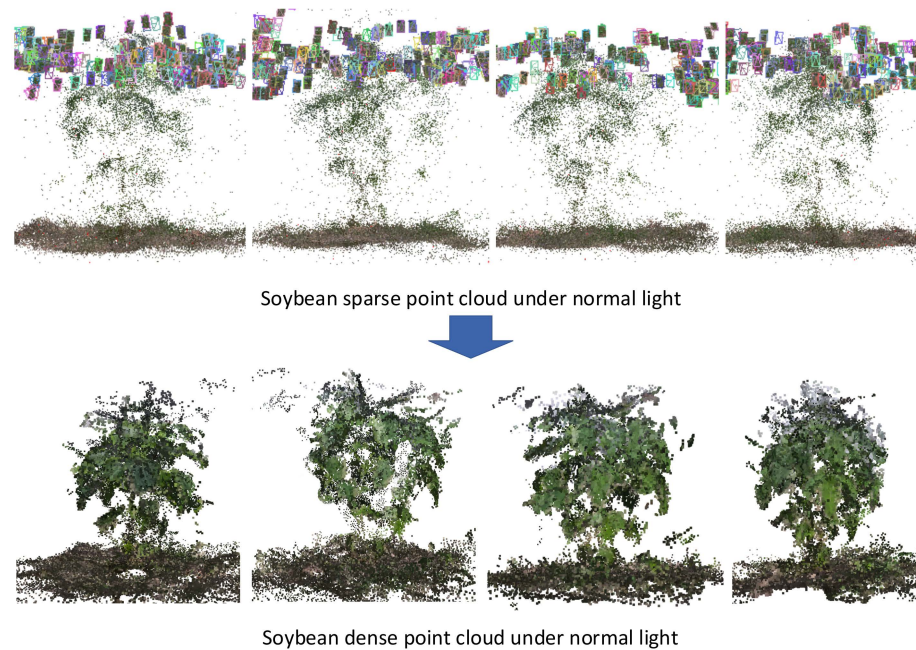


Figure 12. Reconstruction of soybean plant model under normal light.

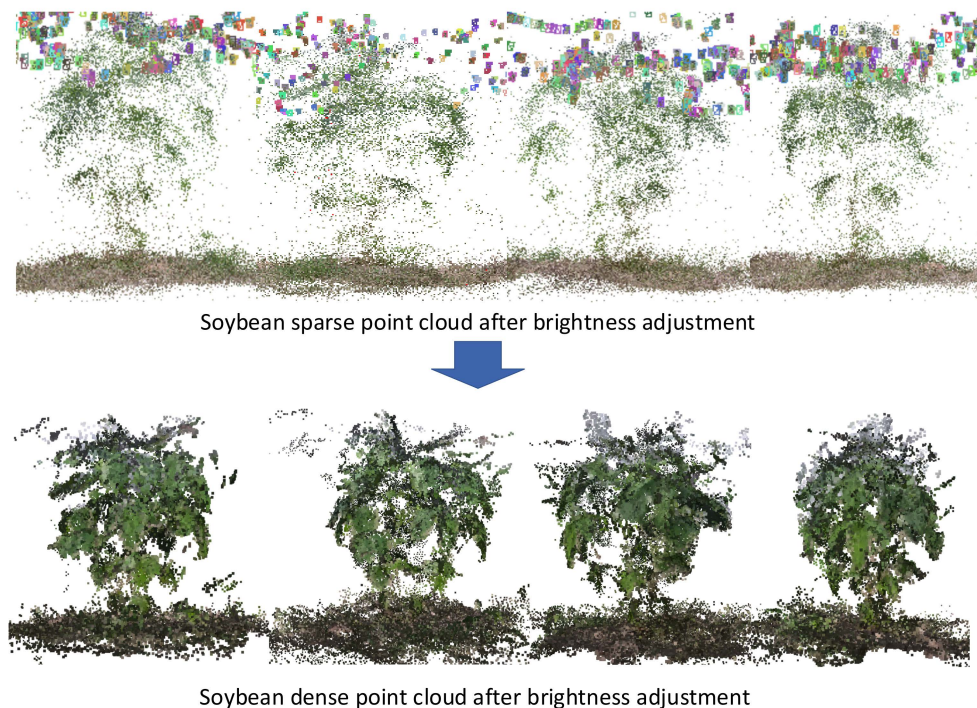


Figure 13. Reconstruction of soybean plant model after brightness adjustment.

5. Conclusions

In order to acquire data on plant growth in low illumination, we enhanced the 3D reconstruction method often employed for crop trait perception for agricultural equipment. We used the EnlightenGAN image enhancement technique to improve low-light photos of soybean plants and highlight their structural characteristics. After picture detection and alignment, we completed the reconstruction of the sparse and dense point clouds of soybeans to actualize the perception of the current growth conditions of soybean plants by agricultural machinery in low-illumination working contexts, such as at night. Using a motion recovery structure method and a multi-view stereo approach, the reconstruction of soybean sparse point clouds and dense point clouds was completed.

We evaluated the impacts of reconstructing soybeans under low illumination, under normal illumination, and after augmentation. We then showed that our method—in which soybean plants are enhanced when exposed to low illumination—performs better at identifying and matching soybean features. Our approach demonstrates that soybean plants under low illumination can be accurately recreated from models employing a high level of refinement, making them nearly comparable to soybean plants grown under normal lighting conditions. With the help of this technique, we hope to increase the range of applications for crop reconstruction and enhance 3D reconstruction performance under more difficult low-light conditions, allowing us to perceive plant growth even in dim lighting. With this effort, the issue of crop reconstruction in low light has taken a stride in the right direction.

Author Contributions: Methodology, Y.H., Y.L., T.H. and S.X.; conceived and designed the experiments, Y.H. and Y.L.; performed the experiments, Y.L. and J.F.; analyzed the data, Y.L.; wrote the paper, Y.H. and Y.L.; funding acquisition, Y.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 61772033, and the Research and the Development Fund of the Institute of Environmental Friendly Materials and Occupational Health, Anhui University of Science and Technology, grant number ALW2021YF03.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Acknowledgments: The authors want to thank the editor and anonymous reviewers for their valuable suggestions for improving this paper.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Pyingkodi, M.; Thenmozhi, K.; Nanthini, K.; Karthikeyan, M.; Palarimath, S.; Erajavignesh, V.; Kumar, G.B.A. Sensor Based Smart Agriculture with IoT Technologies: A Review. In Proceedings of the 2022 International Conference on Computer Communication and Informatics (ICCCI), Chiba, Japan, 1–3 July 2022; pp. 1–7. [\[CrossRef\]](#)
2. Li, X.; Zhang, R. Integrated multi-dimensional technology of data sensing method in smart agriculture. In Proceedings of the 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China, 11–13 December 2020; Volume 9, pp. 2146–2149. [\[CrossRef\]](#)
3. Jiang, Z.; Guo, Y.; Jiang, K.; Hu, M.; Zhu, Z. Optimization of intelligent plant cultivation robot system in object detection. *IEEE Sens. J.* **2021**, *21*, 19279–19288. [\[CrossRef\]](#)
4. Mavridou, E.; Vrochidou, E.; Papakostas, G.A.; Pachidis, T.; Kaburlasos, V.G. Machine vision systems in precision agriculture for crop farming. *J. Imaging* **2019**, *5*, 89. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Zhao, G.; Cai, W.; Wang, Z.; Wu, H.; Peng, Y.; Cheng, L. Phenotypic Parameters Estimation of Plants Using Deep Learning-Based 3-D Reconstruction from Single RGB Image. *IEEE Geosci. Remote Sens. Lett.* **2022**, *19*, 1–5. [\[CrossRef\]](#)
6. Santos, T.T.; De Oliveira, A.A. Image-based 3D digitizing for plant architecture analysis and phenotyping. In *Workshop on Industry Applications, Proceedings of the Conference on Graphics, Patterns and Images, Ouro Preto, Brazil, 22–25 August 2012*; Conference Publishing Series: Berlin/Heidelberg, Germany, 2012; Volume 2012.

7. Santos, T.T.; Koenigkan, L.V.; Barbedo, J.G.A.; Rodrigues, G.C. 3D plant modeling: Localization, mapping and segmentation for plant phenotyping using a single hand-held camera. In *Computer Vision—ECCV 2014 Workshops, Proceedings of the European Conference on Computer Vision, Zurich, Switzerland, 6–7 and 12 September 2014*; Springer: Cham, Switzerland, 2014; pp. 247–263.
8. Bi, J.; Sun, J.; Xu, T.; Lu, J.; Ma, Y.; Qiu, L. A sparse integrative cluster analysis for understanding soybean phenotypes. In *Proceedings of the 2014 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Belfast, UK, 2–5 November 2014*; pp. 1–7. [\[CrossRef\]](#)
9. Li, D.; Shi, G.; Kong, W.; Wang, S.; Chen, Y. A leaf segmentation and phenotypic feature extraction framework for multiview stereo plant point clouds. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2020**, *13*, 2321–2336. [\[CrossRef\]](#)
10. Weyler, J.; Milioto, A.; Falck, T.; Behley, J.; Stachniss, C. Joint plant instance detection and leaf count estimation for in-field plant phenotyping. *IEEE Robot. Autom. Lett.* **2021**, *6*, 3599–3606. [\[CrossRef\]](#)
11. Zhao, Q.; Zhang, Z.; Huang, Y.; Fang, J. TPE-RBF-SVM Model for Soybean Categories Recognition in Selected Hyperspectral Bands Based on Extreme Gradient Boosting Feature Importance Values. *Agriculture* **2022**, *12*, 1452. [\[CrossRef\]](#)
12. Liu, S.; Zhao, L.; Li, J. The applications and summary of three dimensional reconstruction based on stereo vision. In *Proceedings of the 2012 International Conference on Industrial Control and Electronics Engineering, Washington, DC, USA, 23–25 August 2012*; pp. 620–623. [\[CrossRef\]](#)
13. Lin, C.; Hu, F.; Peng, J.; Wang, J.; Zhai, R. Segmentation and Stratification Methods of Field Maize Terrestrial LiDAR Point Cloud. *Agriculture* **2022**, *12*, 1450. [\[CrossRef\]](#)
14. Patel, S.; Goswami, M. Comparative analysis of Histogram Equalization techniques. In *Proceedings of the 2014 International Conference on Contemporary Computing and Informatics (IC3I), Mysuru, India, 27–29 November 2014*; pp. 167–168. [\[CrossRef\]](#)
15. Okado, W.; Goto, T.; Hirano, S.; Sakurai, M. Fast and high-quality regional histogram equalization. In *Proceedings of the 2013 IEEE 2nd Global Conference on Consumer Electronics (GCCE), Las Vegas, NV, USA, 1–4 October 2013*; pp. 445–446. [\[CrossRef\]](#)
16. Parihar, A.S.; Singh, K. A study on Retinex based method for image enhancement. In *Proceedings of the 2018 2nd International Conference on Inventive Systems and Control (ICISC), Coimbatore, India, 19–20 January 2018*; pp. 619–624.
17. Liu, B.; Liu, J. Overview of image denoising based on deep learning. *J. Phys. Conf. Series. IOP Publ.* **2019**, *1176*, 022010. [\[CrossRef\]](#)
18. Sapijaszko, G.; Mikhael, W.B. An overview of recent convolutional neural network algorithms for image recognition. In *Proceedings of the 2018 IEEE 61st International Midwest Symposium on Circuits and Systems (MWSCAS), Windsor, ON, Canada, 5–8 August 2018*; pp. 743–746.
19. Qi, Y.; Yang, Z.; Sun, W.; Lou, M.; Lian, J.; Zhao, W.; Deng, X.; Ma, Y. A comprehensive overview of image enhancement techniques. *Arch. Comput. Methods Eng.* **2022**, *29*, 583–607. [\[CrossRef\]](#)
20. Wei, C.; Wang, W.; Yang, W.; Liu, J. Deep retinex decomposition for low-light enhancement. *arXiv* **2018**, arXiv:1808.04560.
21. Zhang, Y.; Zhang, J.; Guo, X. Kindling the darkness: A practical low-light image enhancer. In *Proceedings of the 27th ACM International Conference on Multimedia, Nice, France, 21–25 October 2019*; pp. 1632–1640.
22. Jiang, Y.; Gong, X.; Liu, D.; Cheng, Y.; Fang, C.; Shen, X.; Yang, J.; Zhou, P.; Wang, Z. Enlightengan: Deep light enhancement without paired supervision. *IEEE Trans. Image Process.* **2021**, *30*, 2340–2349. [\[CrossRef\]](#) [\[PubMed\]](#)
23. Guo, X.; Li, Y.; Ling, H. LIME: Low-light image enhancement via illumination map estimation. *IEEE Trans. Image Process.* **2016**, *26*, 982–993. [\[CrossRef\]](#)
24. Lv, F.; Lu, F.; Wu, J.; Lim, C. MBLEN: Low-Light Image/Video Enhancement Using CNNs. *BMVC* **2018**, *220*, 4.
25. Vijayanarasimhan, S.; Ricco, S.; Schmid, C.; Sukthankar, R.; Fragkiadaki, K. Sfm-net: Learning of structure and motion from video. *arXiv* **2017**, arXiv:1704.07804.
26. Yao, Y.; Luo, Z.; Li, S.; Fang, T.; Quan, L. Mvsnet: Depth inference for unstructured multi-view stereo. In *Proceedings of the European Conference on Computer Vision (ECCV), Munich, Germany, 8–14 September 2018*; pp. 767–783.
27. Guan, H.; Liu, M.; Ma, X.; Yu, S. Three-dimensional reconstruction of soybean canopies using multisource imaging for phenotyping analysis. *Remote Sens.* **2018**, *10*, 1206. [\[CrossRef\]](#)
28. Wang, F.; Ma, X.; Liu, M.; Wei, B. Three-Dimensional Reconstruction of Soybean Canopy Based on Multivision Technology for Calculation of Phenotypic Traits. *Agronomy* **2022**, *12*, 692. [\[CrossRef\]](#)
29. Su, W.H.; Sheng, J.; Huang, Q.Y. Development of a Three-Dimensional Plant Localization Technique for Automatic Differentiation of Soybean from Intra-Row Weeds. *Agriculture* **2022**, *12*, 195. [\[CrossRef\]](#)
30. Wang, L.; Chen, R.; Kong, D. An improved patch based multi-view stereo (PMVS) algorithm. In *Proceedings of the 3rd International Conference on Computer Science and Service System, Bangkok, Thailand, 13–15 June 2014*; Atlantis Press: Paris, France, 2014; pp. 9–12.
31. Karami, E.; Prasad, S.; Shehata, M. Image matching using SIFT, SURF, BRIEF and ORB: Performance comparison for distorted images. *arXiv* **2017**, arXiv:1710.02726.
32. Lhuillier, M. Surface reconstruction from a sparse point cloud by enforcing visibility consistency and topology constraints. *Comput. Vis. Image Underst.* **2018**, *175*, 52–71. [\[CrossRef\]](#)
33. Xu, R.; Guo, M.; Wang, J.; Li, X.; Zhou, B.; Loy, C.C. Texture Memory-Augmented Deep Patch-Based Image Inpainting. *IEEE Trans. Image Process.* **2021**, *30*, 9112–9124. [\[CrossRef\]](#)
34. Mikolajczyk, K.; Schmid, C. A performance evaluation of local descriptors. *IEEE Trans. Pattern Anal. Mach. Intell.* **2005**, *27*, 1615–1630. [\[CrossRef\]](#) [\[PubMed\]](#)

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35. Zhang, Y.; Guo, X.; Ma, J.; Liu, W.; Zhang, J. Beyond brightening low-light images. *Int. J. Comput. Vis.* **2021**, *129*, 1013–1037. [[CrossRef](#)]
 36. Ma, L.; Ma, T.; Liu, R.; Fan, X.; Luo, Z. Toward Fast, Flexible, and Robust Low-Light Image Enhancement. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, New Orleans, LA, USA, 19–24 June 2022; pp. 5637–5646.