RESEARCH ON COLOR CORRECTION METHOD OF GREENHOUSE TOMATO PLANT IMAGE BASED ON HIGH DYNAMIC RANGE IMAGING
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基于高动态范围成像的温室番茄植株图像色彩矫正方法

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ABSTRACT
In this paper, aiming at the need of stable access to visual information of intelligent management of greenhouse tomatoes, the color correction method of tomato plant image based on high dynamic range imaging technology was studied, in order to overcome the objective limitation of complex natural lighting conditions on the stable color presentation of working objects. In view of the color distortion caused by the temporal and spatial fluctuation of illumination in greenhouse and sudden change of radiation intensity in complex background, a calibration method of camera radiation response model based on multi-exposure intensity images is proposed. The fusion effect of multi band image is evaluated by field test. The results show that after multi band image fusion processing, the brightness difference between the recognized target and other near color background is significantly enhanced, and the brightness fluctuation of the background is suppressed. The color correction method was verified by field experiments, and the gray information, discrete degree and clarity of tomato plant images in different scenes and periods were improved.

摘要
本文针对温室番茄智能管理对视觉信息稳定存取的需要，研究了基于高动态范围成像技术的番茄植株图像颜色校正方法，为了克服复杂自然光照条件对工作物体稳定色彩呈现的客观限制。针对温室内光照的时空波动和复杂背景下辐射强度的突变引起的颜色畸变，提出了一种基于多曝光强度图像的摄像机辐射响应模型标定方法。通过现场测试，评价了多波段图像的融合效果。结果表明，经过多波段图像融合处理后，识别出的目标与其它近彩色背景的亮度差异显著增强，背景亮度波动得到抑制。通过田间试验验证了该方法的有效性，提高了不同场景、不同时期番茄植株图像的灰度信息、离散度和清晰度。

INTRODUCTION
With the reduction of agricultural labor force and the rise of labor cost, the labor cost of tomato planting management has increased year by year, which has reached more than 30% of the total production cost *(Albino V.S. et al., 2018)*. In recent years, with the increase of labor cost, the labor cost of tomato planting management has increased to about 45% of the total production cost. The high labor cost has become an objective factor limiting the growth of tomato planting efficiency. In view of the unique advantages of robot in intelligent detection and complex operation, the research and development of agricultural robot which can replace manual operation is an effective way to deal with the current situation from the perspective of engineering technology, aiming at labor-intensive and complex planting management links such as greenhouse tomato picking, pruning, pollination and spraying *(Alvarado K.A. et al., 2020)*. Plant information is an important decision-making basis for intelligent facility gardening control system to achieve accurate control, and it is also a key element of plant phenotypic omics research. Because plant growth information is not only controlled by genetic factors, but also influenced by growth environment, the external three-dimensional geometry and internal physiological information of plants are complex and varied. Tomato plants are clustered and staggered, the working objects grow randomly along the main stem, overlap and block each other, and the space between rows of plants is narrow. There are many problems in collecting and processing images with large field of view, such as small imaging object distance and redundant interference.

Using manual operation for reference, tracking and collecting discrete small-field images in different areas and searching different working objects along the main stem of plants are effective ways to improve the efficiency of working object recognition and location.

With the development and wide application of modern technology, agriculture has entered a new stage of development, and the modernization of agriculture has been paid more and more attention. At the same time, due to the rapid urbanization process and the increasing demand for agricultural products, China attaches great importance to the modern mechanized planting technology of agriculture *(Aznar-Sánchez J. A. et al., 2020)*. Accurately acquiring the visual characteristics of working objects is a necessary prerequisite for intelligent operation of robots. For different management links, the stems, leaves and fruits of tomato plants may be working objects or background interference. However, plants in greenhouse are densely clustered and disorderly, and tomato stems, leaves and green fruits are similar color organs, so it is difficult to realize accurate recognition of plant specific objects based on broad visible light image information *(Bielza P. et al., 2020)*. Visual information is the sensory embodiment of the comprehensive action of the illumination conditions in the working area and the reflection characteristics of the working objects. However, in the agricultural environment, natural illumination fluctuation and complex background interference are the key factors affecting the stable imaging of visual information, which are manifested by the dynamic changes of illumination in time and space and the different radiation characteristics of multiple targets in the field of view. In this paper, aiming at the need of stable access to visual information of intelligent management of tomato in greenhouse, the color correction method of tomato plant image based on high dynamic range imaging technology is studied to overcome the objective limitation of complex natural lighting conditions on the stable color presentation of working objects *(Zhou J. et al., 2018)*. In view of the image color distortion caused by spatiotemporal fluctuation of illumination and mutation of complex background radiation intensity in greenhouse, a calibration method of camera radiation response model based on multi exposure image fusion was proposed.

Visual information acquisition is one of the core technologies to support intelligent production. The plants in greenhouse are dense and disordered, and the stems, leaves and green fruits of tomato are similar color organs. Based on the extensive visible light image information, it is difficult to realize the accurate recognition of plant specific objects. With the continuous growth of the plant, the relative height of the working area to the ground remains unchanged by releasing the hanging line wrapped around the main stem. In the aspect of plant physiological diagnosis, the physiological diagnosis model is mainly built based on multi band two-dimensional spectral image features. Because the two-dimensional image is only a single perspective imaging feature, it cannot reflect all plant features, and cannot reflect the distribution and spatial position of specific physiological features *(Sun G. et al., 2019)*. Traditional manual measurement, loss measurement and low-throughput measurement methods have been unable to meet the needs of intelligent management of modern precision agriculture and the development of plant Phenomics. It is urgent to study highly integrated, high-throughput and high-precision plant phenotypic measurement system. In this paper, high dynamic range imaging technology is used to recover the relative radiation intensity of different objects in the field of view by fusing the image information of different exposures, so as to compensate and correct the color distortion of the image, and then realize the constant presentation of the color of complex background objects. This study can provide a reference for the research on the acquisition of color information of the operation object image under complex lighting conditions.

The plant disease recognition classifier based on probabilistic neural network (PNN) can classify tomato late blight, septal spot, bacterial spot, bacterial ulcer, tomato leaf curl image and tomato healthy plant image by extracting the color, shape and texture features of tomato plant images, then using decision trees sort *(Chaitanya D. N. V. et al., 2018; Chatterjee N. et al., 2019)*. Using machine learning technology, a plant disease severity recognition system can be designed. Combined with support vector machine network and spectral vegetation index, sugar beet disease type diagnosis was realized. An Android application platform was developed to monitor greenhouse vegetables and realize remote observation of vegetable disease degree *(Park G. et al., 2020; Redström J., 2020; Smith H. A. et al., 2019)*. Now the LabVIEW interface for monitoring greenhouse fruits and vegetables has been developed, but these detection applications can only see video. If we want to save historical images for analysis, the storage capacity will be very large, and resources will be wasted. Therefore, it is very important to realize the automatic acquisition system of disease image. By dynamically adjusting the camera exposure gain and white balance parameters, the color of petal image can be presented stably *(Siddique M.A.A. et al., 2020).*

Combining depth vision technology with multispectral imaging technology, tomato plants in greenhouse were studied *(Tan G. et al., 2017).* The RGB-D images and multispectral images of each plant were collected in the same imaging room at the same time, and the multispectral reflectance of each plant was recorded in the depth coordinate system by using the principle of phase correlation *(Lee P. U. et al., 2018).*

The problem of kiwifruit night vision recognition is solved by setting foreground led complementary light source, highlighting the boundary of overlapping targets and reducing background interference. By analyzing the color quality of the target image in real time and dynamically adjusting the control parameters of the filling light source, the low energy consumption and high efficiency exposure compensation is realized. The litchi image preprocessing method based on Retinex image enhancement algorithm overcomes the problem of uneven brightness of camera field of view under natural light. By using Caffe framework and deep convolution network, 14 kinds of diseases are recognized, and good results are achieved. Support vector machine (SVM) was used to classify healthy and ill conditioned images of soybean leaves. The main steps of the experiment are: image acquisition, leaf extraction under complex background, statistical analysis and classification, and finally good results were achieved. The performance of several machine learning techniques in pattern recognition and classification of leafy plant diseases is compared. Finally, the conclusion that support vector machine has more advantages is drawn.

MATERIALS AND METHODS

Temporal and spatial fluctuation of light parameters

As tomato is a kind of fruit and vegetable with high sales value and high yield demand, this paper takes tomato plant diseases as the research object, and processes 300 images of tomato leaf gray mold, late blight, powdery mildew and normal leaves. GMM (Gaussian Mixture Model) is used to segment the image background, HSI (Hue Saturation Intensity) algorithm is used to segment the diseased spots, and then three kinds of change model algorithms are used to extract color features. At present, the target recognition and classification methods based on spectral characteristic images mainly take the strongest reflection band of the target as the imaging band, only emphasize the brightness of the target area image, and lack the fusion of the background weak reflection band image, which cannot fully achieve the purpose of highlighting the strong reflection target and diluting the weak reflection background interference. Registration and mosaic of discrete field images is a necessary way to obtain the overall morphological characteristics of tomato stem. Camera pose matching obtains the spatial pose parameters of camera in real time, and analyzes the transformation relationship of target shape from different perspectives based on perspective imaging principle. Influenced by the change of direction and intensity of solar illumination during the day, the illumination parameters in semi-open greenhouse show temporal and spatial dynamic changes. According to the internal parameters of Kinect sensor, the sensor converts RGB-D images from different angles into three-dimensional point clouds.

The change of illumination intensity in greenhouse is the main factor that leads to the color variation of the target image. Accurate analysis of dynamic radiation intensity information in different areas of the camera field of view is the premise of compensating and correcting the fluctuation of ambient illumination. Figure 1 is a three-dimensional schematic diagram of color.

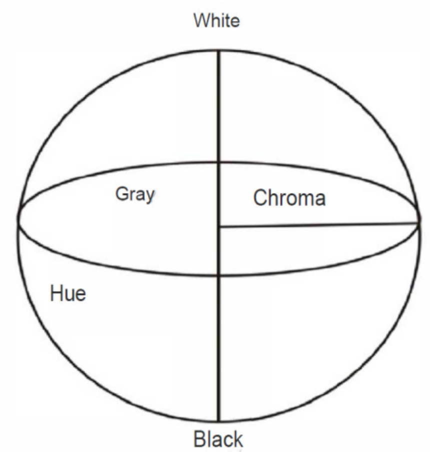

Fig. 1 - Color stereo schematic

Figure 2 shows two images collected under different exposure intensities. In Figure 2a, the ceiling sky and wall colors are normal, and the tomato plant area is underexposed. In Figure 2b, the color of tomato plants is normal, and the ceiling and wall areas are overexposed.

(a) Underexposure (b) Overexposure

Fig. 2 - Image color distortion caused by the difference in target radiation characteristics

Because each spatial coordinate point contains RGB value and reflectivity value of each band, the multi-modal 3D point cloud model reconstruction is realized when realizing 3D point cloud model reconstruction. Single spectral feature data lacks target spatial information, so it is difficult to be used as the basis of visual servo control, and is mostly used for the classification of biological tissue components and physiological characteristics such as pests and diseases, weed species and leaf density. The spectral image data obtained by imaging technology is the comprehensive embodiment of the spectral reflection characteristics of the target and its spatial position information, which can be used as the basis for the robot to recognize the target and accurately target the operation. Kinect sensors collect RGB images and depth images.

To realize multi-modal 3D reconstruction of tomato plants, it is necessary to align the multispectral reflectance of the plants to the depth coordinates, that is, each 3D spatial coordinate contains RGB values and multispectral reflectance. There are mainly displacement, rotation angle and scaling transformation problems between SOC710 image and Kinect image. Collect RGB-D images of the electric turntable surface from two perspectives, identify the yellow and red calibration point cloud coordinates of the turntable surface from each perspective according to the color threshold, calculate the calibration point center, and calculate the center coordinate and normal vector of the turntable rotating shaft according to the center of gravity. In view of the differences in the components of different organs, such as stems, leaves and fruits, classification and recognition according to their specific spectral characteristics is an effective way to solve the problem of visual recognition of plant objects with similar colors.

Mutation of radiation intensity in complex background

In view of the non-uniform structure of the object to be measured, and its surface morphology, composition and texture are irregular, spectral data are collected for each sample for 5 times, and the average value is the spectral measurement data of a single sample. The spectral characteristic curves of stems, leaves and green fruits of tomato plants were obtained by filtering, denoising and averaging the spectral data of various samples. The radiation characteristics of different targets are different under the complex background of greenhouse, among which the radiant brightness of the near tomato plant is greatly different from that of the far greenhouse ceiling and wall. In addition, there is a sudden change in brightness between the shadow area projected by the steel structure at the top of the greenhouse and the direct sunlight area.

However, the range of radiation fluctuation in the field of view presented by the camera imaging chip is limited, which will lead to overexposure and underexposure in the image area under specific exposure intensity, resulting in distortion of target color information. By rotating the wheel, the filter in front of the camera lens can be switched to collect images in different bands. 180W halogen lamp is selected as the light source, and 5000lx radiation intensity is formed in the field of view of the camera to overcome the influence of illumination fluctuation in the experimental environment.

Under the radiation environment of the same light source, the illumination intensity of different bands is different, and the sensitivity of the camera imaging chip to different bands is also different. In order to make the image brightness correspond to the target spectral reflection intensity, it is necessary to collect images of different bands for brightness correction. Figure 3 shows the system structure of plant digital image analysis based on high dynamic range.

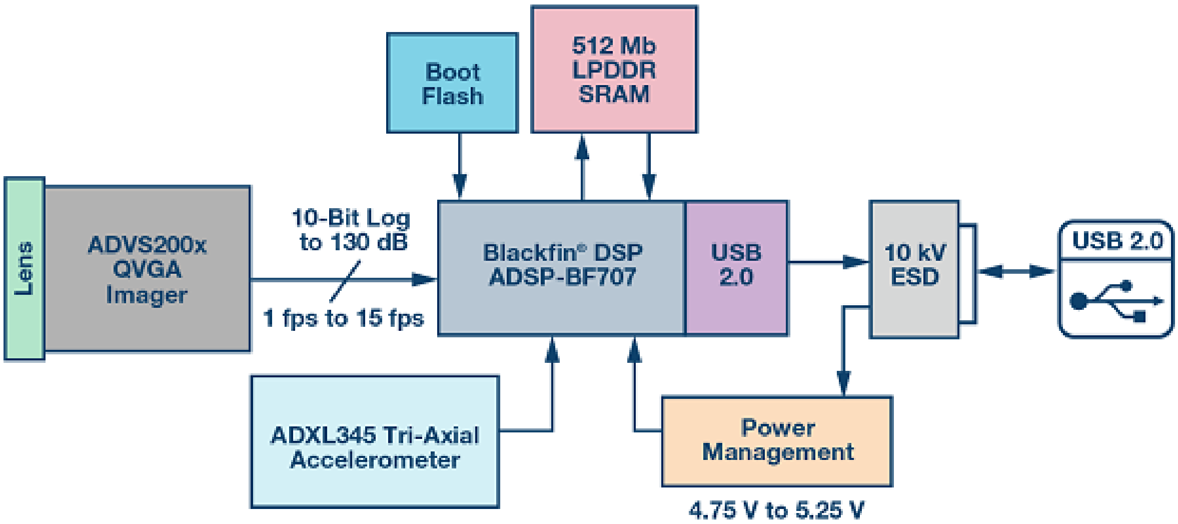

Fig. 3 - The structure of the plant digital image processing and analysis system

The Gaussian kernel is the only kernel that can generate multi-scale space. The scale space of an image, $L(x,y,\sigma)$ is defined as the original image $I(x,y)$ and a variable-scale two-dimensional Gaussian function $G(x, y, \sigma)$ convolution operation, as shown in formula (1)(2):

$$G(x_i, y_i, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\sigma^2} \right) \tag{1}$$

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{2}$$

The Gaussian difference function $D(x, y, \sigma)$ can be calculated by the difference between two adjacent scale images with a constant multiplication factor k, as shown in equation (3):

$$D(x, y, \sigma) = [G(x, y, k\sigma) - G(x, y, \sigma)] * I(x, y) = L(x, y, k\sigma) - L(x, y, \sigma) \tag{3}$$

Single global exposure control can easily lead to color distortion of foreground and background objects, which is an objective limitation for cameras to obtain images of greenhouse tomato plants. In view of this, it is an effective way to correct exposure distortion in image areas by fusing multi-exposure image information to restore radiation intensity in different areas of the field of view.

The flow chart of the image processing system is shown in Figure 4.

The standard color plate can be pushed into a specific position of the camera field of view near the tomato plant by a mechanical device. By triggering the acquisition mode, the camera collects one image of tomato plant and standard color plate in the same wave band, and the camera exposure parameters remain unchanged during the acquisition process. Under the same light source radiation environment, the illumination intensity in different bands is different, and the sensitivity of camera imaging chips to different bands is also different. In order to make the image brightness correspond to the target spectral reflection intensity, it is necessary to collect images in different bands for brightness correction. The standard color plate can be pushed into a specific position of the camera field of view near the tomato plant by a mechanical device. By triggering the acquisition mode, the camera collects one image of tomato plant and standard color plate in the same wave band, and the camera exposure parameters remain unchanged during the acquisition process. The purpose of multi-band image data fusion is to make the target pixel area stand out from diverse backgrounds and keep the brightness of non-target background areas balanced, so as to reduce the difficulty of target area segmentation.

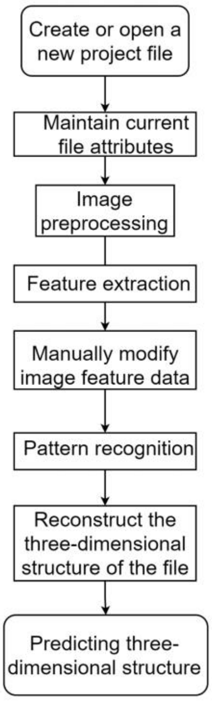

Fig. 4 - Image processing system flow

RESULTS

The purpose of contour extraction and contour tracking is to obtain the external contour features of the image. On this basis, a certain method is applied to express the characteristics of the contour to prepare for the shape analysis of the image. After multi-band image fusion processing is performed on specific targets of tomato stems, leaves, and green fruits, the pixel brightness of the targets with similar color backgrounds all show obvious differences. In the original optimal imaging band and the fusion result image, 500 pixels were selected for the stem, leaf and green fruit area respectively. After multi-band image fusion processing is performed on specific targets of tomato stems, leaves, and green fruits, the pixel brightness of the targets with similar color backgrounds all show obvious differences. In the original optimal imaging band and the fusion result image, 500 pixels were selected for the stalk, leaf and green fruit area respectively, and the grayscale difference between green fruit-leaf, stem-green fruit and stem-leaf was calculated. Since the height of the visual field of the vision system is about 400 mm, in order to cover the height of the main stem of the work area, the camera pan/tilt is set to automatically adjust twice from the horizontal initial posture, and 3 images are tracked and collected for each tomato, and in this sequence of images the morphology of the main stem is spliced and measured. The tomato plant stem and leaf features are completely segmented, but some background and reference template edges are also segmented and retained. Therefore, the segmented binary image needs to be further filtered to remove information other than tomato plants.

In view of the fact that the greenhouse light fluctuation is mainly reflected in the change of light intensity, this article focuses on the correction of the image color brightness in order to achieve the purpose of reconstructing the target true color. The CIE XYZ color model is a three-primary color system designed based on the human eye's perception of the color of visible light sources. All visible colors can be represented by three-color values (X, Y, Z). The color description of digital image acquisition and display is based on the ITU709 standard.

The conversion formula of image RGB color information and CIE XYZ color model is:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.4086 & 0.3581 & 0.1802 \\ 0.2099 & 0.7204 & 0.0731 \\ 0.0217 & 0.1189 & 0.9534 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

in which X and Z are CIE XYZ image chroma components, Y is CIE XYZ image brightness components, and R, G and B are digital image color components.

The sequence exposure images of different scenes in specific periods are shown in Figure 5.

Fig. 5 - Sequence exposure images of different scenes at specific times

In order to make up for the deficiency of the existing contraction function, a new curve contraction function is constructed to make the estimated value continuous at the threshold. With the increase of radial component, it can reach and exceed the true value.

The contraction trend of adaptive nonlinear curve is shown in Figure 6.

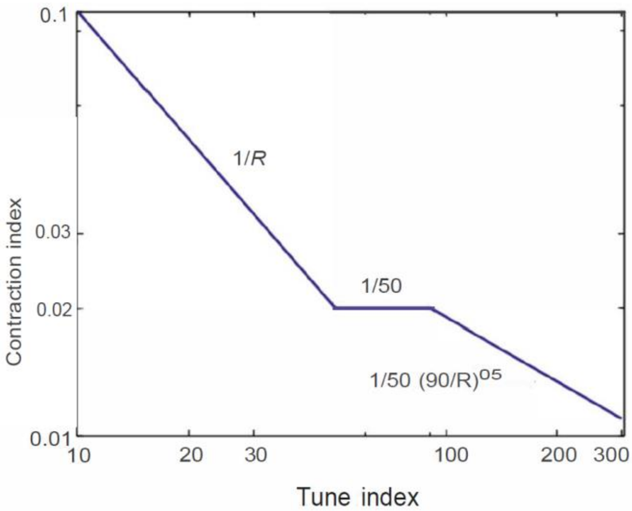

Fig. 6 - The shrinking trend of adaptive nonlinear curve

The S-curve function is used to map the high dynamic image data to the gray scale range of 0-255. The brightness of the compressed image is:

$$Y_i^d = \frac{255 \log_5 \left(E_i / \overline{E} + 1\right)}{\lg\left(E_{\max} / \overline{E} + 1\right)\left(1 + \exp\left(-\log_2 E_i\right)\right)} \tag{5}$$

In which:

$$\overline{E} = \exp\left(\frac{1}{N} \sum_{i=1}^{N} \ln E_i\right) \tag{6}$$

Where E_{max} is the maximum brightness of the high dynamic image, Y_i^d is the image brightness after compression, and $\overline{E}$ is the average brightness of the high dynamic image. Based on the radiation characteristics of the scene in Figure 7, the calibrated camera radiation response curve is shown in Figure 7.

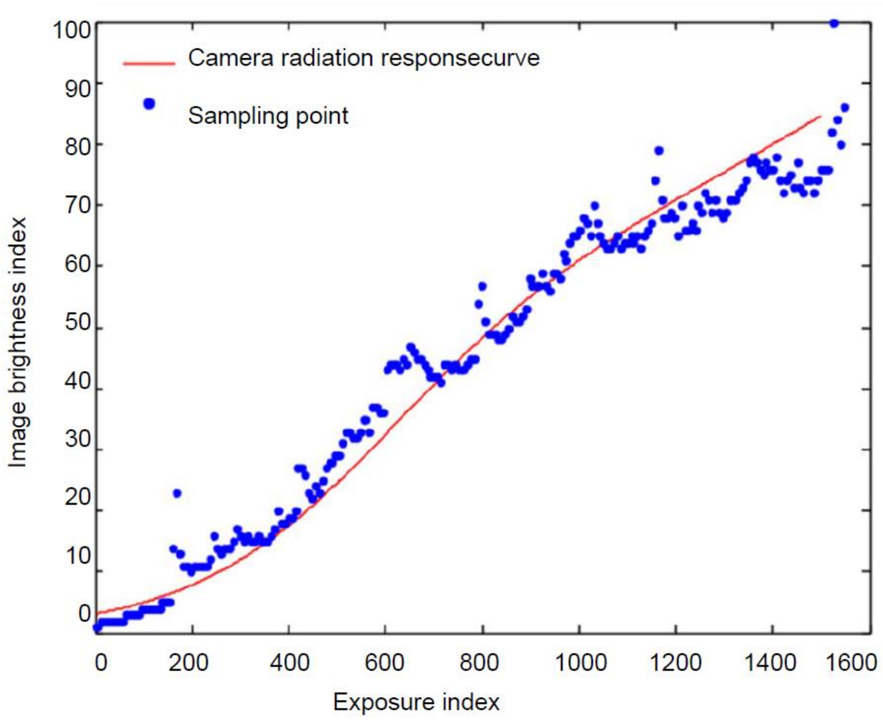

Fig. 7 - Camera radiation response curve

In order to quantitatively evaluate the effect of image correction, information entropy and average gradient are used as evaluation indexes to evaluate the gray information content, dispersion degree and clarity of the image before and after color correction.

Statistics of evaluation parameters of original and corrected images of tomato plants in different scenes and periods are shown in Table 1 and Table 2 respectively.

Table 1

Image information entropy statistics

t/ms	Scene 1: Sunlight scene				Scene 2: Cloudy scene			
	8:00	10:00	12:00	14:00	8:00	10:00	12:00	14:00
0.02	4.78	4.76	4.60	4.61	3.85	3.45	3.36	3.46
0.04	5.23	5.01	4.89	4.89	3.73	3.55	3.32	3.36
0.06	4.77	4.82	4.69	4.70	3.55	3.47	3.17	3.42
0.08	4.73	4.84	4.18	4.33	3.55	3.46	3.23	3.33

Table 2

Image average gradient statistics

t/ms	Scene 1: Sunlight scene				Scene 2: Cloudy scene			
	8: 00	10: 00	12: 00	14: 00	8: 00	10: 00	12: 00	14: 00
0.02	0.031	0.039	0.039	0.039	0.021	0.025	0.026	0.030
0.04	0.036	0.041	0.041	0.042	0.025	0.031	0.035	0.035
0.06	0.029	0.033	0.033	0.033	0.024	0.029	0.030	0.031
0.08	0.035	0.039	0.038	0.038	0.028	0.033	0.033	0.032

From the statistical results, the brightness of the image area of tomato stems, leaves and fruits increases with the increase of imaging wavelength, that is, the intensity of plant reflection is greater in the long-wave area. The transmitted sunlight forms an obvious spot area in the short-wave image, but the brightness is not obvious in the long-wave image area. Since the boundary is continuous, each boundary point can be represented by the angle formed by this boundary point to the previous boundary point.

Therefore, the following tracking criteria can be used, that is, starting from the first boundary point, define the initial search direction to be along the upper left, if the upper left is a black point, it is the boundary point, otherwise the search direction is rotated clockwise by 45°.

Since the main stem is suspended in space and flexibly bent, and the contact and collision during manual measurement may change its natural shape, manual measurement results still cannot accurately reflect the true natural shape of the main stem. After multi-band image fusion, the main areas of similar color targets can be segmented from the background through conventional automatic segmentation algorithms. Nevertheless, the segmentation results for stems and fruits show that the specular reflection area on the fruit surface becomes the main error segmentation area. Therefore, to overcome the smooth surface specular reflection of the tomato fruit surface to improve the target imaging effect is the focus of further research.

CONCLUSIONS

Plant information is an important decision-making basis for intelligent facility gardening control system to achieve accurate control, and it is also a key element of plant phenotypic omics research. In this paper, aiming at the problem of fluctuation of light intensity in greenhouse environment and sudden change of brightness in complex background, an image color correction method based on high dynamic range imaging is proposed, which effectively overcomes the problem of color distortion of tomato plant image under global exposure.

The method of tracking and measuring the main stem of a plant based on a binocular pan/tilt camera can realize the collection and splicing of images in discrete areas, and measure the three-dimensional morphological parameters such as the length, height and growth angle of the visible area. There is a linear correlation between the manual measurement results of living plants and the automatic measurement results of images. In gray-scale transformation enhancement, histogram specification purposefully enhances some gray levels and improves the visual effect of disease images, but this enhancement method does not play a role in suppressing various noises.

The relative relationship of brightness of similar color target image obtained by multi-band image online acquisition system is consistent with its spectral reflection intensity. In this paper, high dynamic range imaging technology is used to restore the relative radiation intensity of different targets in the field of view by fusing the image information with different exposures, so as to compensate and correct the image color distortion, and then realize the constant presentation of complex background target color.

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