

Review of Machine-Vision-Based Plant Detection Technologies for Robotic Weeding

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Abstract

Controlling weeds with reduced reliance on herbicides is one of the main challenges to move toward a more sustainable agriculture. Robotic weeding is a thought to be a viable way to reduce the environmental loading of agrochemicals while keeping the operation efficiency high. One of the key technologies for performing robotic weeding is automatic detection of crops and weeds in fields. This paper presents an overview on various methods for detecting plants based on machine vision, mainly concentrating on two main challenges: dealing with changing light and crop/weed discrimination. To overcome the first challenge, both physical and algorithmic methods have been proposed. Physical methods can result in a more cumbersome machine while algorithmic methods are less robust. For crop/weed discrimination, deep-learning-based methods have shown obvious advantages over traditional methods based on hand-crafted features. However, traditional methods still hold some merits that can be leveraged to deep-learning-based methods. With the fast development of hardware technologies, researchers should take full advantage of advanced hardware to ease the algorithm design. In the future, the identification of crops and weeds can be more accurate and fine-grained with the support of online databases and computing resources based on the advances in artificial intelligence and communication technologies.

Full Text

Preamble

Review of Machine-Vision-Based Plant Detection Technologies for Robotic Weeding

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Abstract

Controlling weeds with reduced reliance on herbicides is one of the main challenges in moving toward more sustainable agriculture. Robotic weeding is thought to be a viable way to reduce the environmental loading of agrochemicals while maintaining high operational efficiency. One of the key technologies for robotic weeding is the automatic detection of crops and weeds in fields. This paper presents an overview of various methods for detecting plants based on machine vision, focusing on two main challenges: dealing with changing light conditions and crop/weed discrimination. To overcome the first challenge, both physical and algorithmic methods have been proposed. Physical methods can result in more cumbersome machinery, while algorithmic methods are less robust. For crop/weed discrimination, deep-learning-based methods have shown clear advantages over traditional methods based on hand-crafted features. However, traditional methods still hold some merits that can be leveraged to improve deep-learning-based approaches. With the rapid development of hardware technologies, researchers should take full advantage of advanced hardware to ease algorithm design. In the future, the identification of crops and weeds can become more accurate and fine-grained with the support of online databases and computing resources based on advances in artificial intelligence and communication technologies.

Index Terms—Weed control, Precision agriculture, Machine vision, Image processing.

I. Introduction

Weeds are a major menace in crop production as they compete with crops for nutrients, moisture, space, and light. Every year, weed infestation causes huge losses in agricultural production worldwide, despite large investments of labor, herbicides, and energy. Currently, chemical weeding remains the dominant method of weed control in agricultural production systems. By spraying herbicides evenly over entire fields, most weeds can be quickly eliminated, which is cost-effective and efficient. However, with increasing emphasis on food safety and environmental protection, minimizing the use of chemical herbicides is a general trend. By automatically removing weeds through non-chemical means

or applying herbicides precisely, robotic systems are regarded as a viable alternative to decrease CO₂ emissions and agrochemical loading in conventional agriculture.

To achieve high-performance robotic weed control, especially for in-row treatment, crops and weeds must be correctly detected and located. Extensive plant detection and localization methods have been explored by researchers worldwide, based on RTK GPS (Real-time Kinematic Global Positioning Systems), machine vision, laser sensors, X-ray, ultrasound, and other technologies.

RTK GPS systems can provide absolute positions of crop plants and weeds for robotic weeding, provided that crops are planted using an RTK GPS-guided planting system or a map of crop/weed distribution has been created before treatment [?, ?]. RTK-GPS-based weeding systems are not adversely affected by weed density, shadows, or missing plants, but can be affected by satellite distribution, weather conditions, radio interference, and geography. Some researchers have investigated approaches for detecting plants with laser sensors [?, ?, ?]. Laser sensors usually have relatively high prices and require complex procedures to process the output 3D point clouds. X-ray can be used for crop detection since a plant's main stem absorbs X-ray energy [?]. However, the safety and cost of X-ray systems are major concerns, and very few studies have been reported in this domain.

With the rapid development of computer technology, graphics, and image processing technology, machine vision has been widely applied to various agricultural tasks. Autonomous guidance along crop rows, individual plant detection, and weed mapping for robotic weed control have been important areas of machine vision application. Since machine vision can provide abundant information about targets—such as color, shape, texture, and depth—with considerably high accuracy and relatively low cost, the majority of past research on plant detection has been based on machine vision.

Field environments are complex and changeable unstructured settings affected by climate, time, agronomic measures, and other factors. Therefore, researchers must consider the requirements of field weeding operations as well as the characteristics of environments when designing machine vision systems and image processing algorithms.

One major concern for machine-vision-based systems applied in robotic weed control is their susceptibility to natural light, which changes over time. This primarily creates difficulties in segmenting vegetation (crops and weeds) from the background (bare soil, rocks, and residues) and in feature extraction. Another challenge is distinguishing between crops and weeds that have similar appearances. Furthermore, it can be exceptionally challenging to identify individual plants when severe occlusion occurs between them. Thus far, numerous efforts have focused on: 1) coping with varying outdoor lighting conditions, and 2) crop/weed discrimination. Therefore, we propose a review of studies on machine-vision-based plant detection according to how they address these

challenges.

II. Dealing with Variable Natural Light

When machine vision systems operate in field environments, the intensity and spectral content of daylight may change over time. On sunny days, image processing becomes more difficult due to the presence of highlights and shadows in images. Thus, it is necessary to design systems and algorithms that are robust to changing light conditions.

A number of researchers have investigated methods for improving the performance of machine vision systems under varying natural light, such as using shading, paying special attention to selecting segmentation indices, or developing other approaches to make image processing algorithms more robust to variable illumination.

A. Shading and Artificial Lighting

In many studies, physical methods like artificial lighting and shading were used to achieve constant light conditions. The weed identification system described in [?] employs three special plant lights with 400 W metal halogen lamps to illuminate the field of view, and a lightproof polyethylene film cover to block out natural light, as shown in Figure 1: see original paper. The commercial robotic weeding system Steketee IC [?] has a camera and high-power LED light mounted under a metal hood for monitoring each crop row, as depicted in Figure 1: see original paper. The metal hood ensures no effect from sunlight or shadows. The BoniRob agricultural field robot [?] in Figure 1: see original paper also uses shading and artificial lighting to control the illumination of the operational area.

Some systems only employ artificial lighting to maintain relatively stable illumination conditions. The Robovator intra-row weeding system [?] has a halogen lamp installed behind each camera to keep lighting relatively constant, as shown in Figure 1: see original paper. However, no cover is equipped over the image acquisition area. The AgBot II [?, ?] is equipped with a pulsed lighting module behind the camera to improve the quality of acquired images, as shown in Figure 1: see original paper. For these two systems, natural light reflected from the environment and shadows from mechanical components may still affect the machine vision systems.

For vision systems with narrow fields of view, contriving mechanical solutions and artificial lighting is an effective way to cope with changeable natural light and reduce the difficulty of developing image processing algorithms. However, some weeding systems, such as the Garford Robocrop InRow Weeder [?] shown in Figure 1: see original paper, use each camera to monitor multiple crop rows. To obtain a wide enough field of view, the camera must be installed at a high position. In that case, shading and artificial lighting can result in a more cumbersome and expensive machine. Consequently, many researchers persistently

work on devising image processing algorithms that are more robust to variable illumination.

B. Image Processing Considering Illumination Change

In most plant detection methods, vegetation (crops and weeds) and soil background are first segmented, followed by crop/weed discrimination and localization procedures. Therefore, the segmentation of vegetation and soil background is directly affected by changes in illumination conditions.

Usually, the segmentation procedure consists of two main steps: 1) design or select color indices to convert color images to grayscale images; and 2) apply an appropriate threshold to distinguish vegetation from soil. The excessive green (ExG), normalized excessive green (NExG) indices [?], color index of vegetative extraction (CIVE) [?], and normalized difference vegetation index (NDVI) [?] are the most commonly used vegetative indices. The NExG takes into account the light intensity of each pixel to attenuate the effect of illumination variation, while NDVI introduces a ratio between the amount of near-infrared light and red light reflected by objects. For adaptive segmentation threshold selection, Otsu's method [?] is the most widely used.

Many researchers have tried other color indices and segmentation methods, achieving good results. To overcome the influence of partial shadows in images, Marchant et al. [?, ?] proposed a shadow-invariant transformation F for image graying based on the Commission Internationale de l' Eclairage daylight model. Zheng et al. [?] developed an image segmentation method based on the mean-shift algorithm and a BP neural network, which can segment vegetation and soil background well in both shaded and non-shaded images. The drawback of this method is that it is too time-consuming.

To deal with the specular reflection of crop leaves under strong illumination, Ye et al. [?] developed a vegetation extraction method using probabilistic superpixel Markov random field, which achieved outstanding performance on images where highlights and shadows appeared.

All the methods mentioned above have been tested on images collected under natural light, and some good results have been obtained. However, field conditions are complex and changeable; it is difficult for one index or segmentation method to have universal applicability. In more challenging cases, such as processing images with partial shadows collected at noon with strong sunlight, further tests and verifications are needed to improve existing methods and develop more generalized and robust ones.

III. Crop/Weed Discrimination

In the procedure of crop and weed detection for robotic weeding, the most important step is to correctly separate crop plants from weeds. Because of the various and irregular distribution of weeds and the similarity between crops and

weeds in physical characteristics, discrimination between them is not an easy task. Traditional methods usually take advantage of differences in features like color (or spectral characteristics), shape, texture, size, height, and distribution between crops and weeds. With the rise of deep learning technology, ever-more researchers are applying deep neural networks to perform end-to-end crop/weed recognition.

A. Color-Based Crop/Weed Discrimination

Although most crops and weeds are green, their spectral characteristics differ. Intuitively, they present different shades of green. The extraction of color features is relatively simple and fast, which is advantageous for distinguishing crops and weeds based on color differences.

Nieuwenhuizen et al. [?] developed two color-based machine vision algorithms for volunteer potato detection in sugar beet fields, using an Adaptive Neural Network and a K-Means clustering/Bayes classification scheme. Piron et al. [?] added interference filter combinations to a black-and-white camera to collect images and studied the best combination of filters to distinguish carrots from weeds. Li et al. [?] transformed color field images into HSI color space and constructed a Mahalanobis distance classifier to perform pixel-wise crop/weed classification based on differences in hue and saturation. Hamuda et al. [?] proposed an algorithm for detecting cauliflowers from video streams, which segments cauliflowers from weeds and soil under different illumination conditions using morphological erosion and dilation within HSV color space. Zheng et al. [?] selected nine optimal color features with principal component analysis (PCA) and built a support vector classifier to differentiate maize from mixtures of different weeds. They demonstrated that the method was stable under various weather conditions and over time.

Color-feature-based methods are usually less complex than texture- or shape-feature-based methods. When the colors (spectral characteristics) of the plants to be distinguished are comparatively close, using color features alone cannot achieve satisfactory discrimination results. In more studies, researchers have combined color with other features for crop/weed discrimination.

B. Shape-Based Crop/Weed Discrimination

Since the leaf shapes of field plants are varied, they provide an important information source to visually distinguish different plants. Therefore, many methods have been designed to extract shape features for discriminating crops and weeds.

Cho et al. [?] developed a machine vision system for weed detection in a radish farm. They extracted eight shape features, among which aspect ratio, elongation, and perimeter-to-broadness ratio were selected as significant discriminant variables. Using an artificial neural network (ANN) as a classifier, their method achieved successful recognition rates of 93.3% for radish and 93.8% for weeds. Neto et al. [?] used the Elliptic Fourier descriptor as the shape feature of plant

leaves, selected the Fourier coefficients with the best discriminatory power by PCA, and used canonical discriminant analysis to classify soybean, sunflower, redroot pigweed, and velvetleaf plants. Swain et al. [?] established the shape model of two-leaf growth stage nightshade plants and used an automated active shape matching technique to classify plants into crops and weeds. Joen et al. [?] extracted five normalized shape features of maize and weeds, including length/width, height/perimeter, perimeter/area, width/area, and length/area, and used an ANN classifier to identify weeds from crop plants. Wong et al. [?] presented a method for weed identification using a combination of features including fractal, shape features, and moment invariants. The Genetic algorithm was adopted to optimize feature selection and the support vector machine (SVM) classifier. However, this method was designed with the assumption that weeds are young and non-occluded. Lottes et al. [?] computed nine statistical features, seven shape features, and two other features, and exploited a random forest classifier to separate sugar beets from weeds. Bakhshipour et al. [?] tried to integrate shape feature sets including Fourier descriptors and moment invariant features to establish a pattern for sugar beets and weeds. For crop/weed classification, they compared SVM and ANN based on the plant pattern. Both classifiers achieved accuracies over 90%, while SVM performed better.

Shape-based methods can be very effective when plant leaves are intact and non-occluded. When there are overlaps and damage to plant leaves, the difficulty of extracting shape features increases significantly. In addition, due to the wide variety of crop and weed species, there is a lack of a generalized set of shape features for crop/weed discrimination.

C. Texture-Based Crop/Weed Discrimination

In field images, plants present differences in texture due to disparities in leaf size, contour, vein distribution, and density. Therefore, it is possible to use texture features to distinguish between crops and weeds.

Tang et al. [?] studied the classification and recognition of broadleaf and grass weeds, exploiting a Gabor wavelet-based algorithm to extract spatial frequency texture features of the weeds and a feedforward ANN to process the extracted feature vectors for weed classification. Wu et al. [?] proposed a method for identifying weeds in corn fields at early growth stages. The texture features of weeds and corn seedlings were obtained using Gray Level Co-occurrence Matrix (GLCM) and statistical properties of field images. PCA was used to select the texture features with prior contributions, followed by a crop/weed classification procedure using SVM.

To improve the accuracy of real-time *Rumex obtusifolius* detection, Hiremath et al. [?] explored two different sets of visual texture features corresponding to GLCM and Laws' filter masks. They concluded that GLCM features including contrast, entropy, and correlation were the best among the two sets, showing a high degree of robustness to lighting conditions and weed size. Bakhshipour et

al. [?] explored the potential of using wavelet texture features for weed detection in sugar beets. They extracted GLCM texture features for each multi-resolution field image produced by single-level Haar discrete wavelet transform. PCA was used to select 14 features from the 52 extracted texture features, and an ANN was employed for classification.

Texture-based methods are useful when there is a significant difference between the textural frequencies of plant canopies. Similar to shape features, texture feature extraction is a relatively complex and computationally intensive image processing procedure. Commonly, feature selection and dimension reduction algorithms are used to select features with better contributions as input for a classifier. The advantage of texture features is that they are more robust than shape features for separating and recognizing crops and weeds when their leaves are mutually occluded.

D. Height-Based Crop/Weed Discrimination

Usually, the heights of crop plants in the same field plot are very similar, while differing from those of weeds. Especially in transplanted crop fields, crop plants have obvious height advantages over weeds. Stereo vision systems can obtain depth information within the field of view, providing an approach to segment crops and weeds based on their heights.

Piron et al. [?] proposed a method combining multispectral and stereoscopic information for weed detection in carrots. They extracted five features including three spectral bands data, height, and number of days after sowing, and employed quadratic discriminant analysis for crop/weed discrimination. Chen et al. [?] developed a machine vision system for detecting intra-row weeds. The crop detection algorithm applied height and plant spacing information to differentiate crops from weeds. Gai et al. [?] developed a crop recognition and localization algorithm using both 2D and 3D data from a Kinect v2 sensor. The 2D color and textural data were fused with 3D point cloud data, and crop morphological models were developed for crop recognition against weeds at different growth stages. Wang et al. [?] extracted 16 morphological features and two texture features in 2D field images and calculated plant height based on binocular images. Using the max-min ant system algorithm, six optimal morphological features were selected, which were input into an SVM model together with the two texture features and height feature for distinguishing maize seedlings from weeds. Li et al. [?] applied a 3D time-of-flight (ToF) camera to a crop recognition system for broccoli and green bean plants under weedy conditions. They extracted 2D and 3D features including gradient of amplitude and depth image, surface curvature, amplitude percentile index, normal direction, and neighbor point count in 3D space, and developed a segmentation algorithm for each crop according to the 3D geometry and 2D amplitude. The method achieved high segmentation accuracy under challenging conditions. However, the low resolution of the ToF camera limited precision. Ge et al. [?] proposed a method for broccoli seedling recognition in weedy broccoli fields based on Binocular Stereo Vision

and a Gaussian Mixture Model. The method achieved a correct recognition rate of 97.98% for 247 pairs of 640×480 pixel broccoli images with prominent weed growth. Processing time for each pair of images was 578 ms.

The advantage of stereo-vision-based methods is obvious as they can utilize information from 2D images while introducing plant height. On the other hand, they have the drawback of requiring complex and time-consuming procedures for processing 3D point cloud data.

E. Distribution-Based Crop/Weed Discrimination

As most crops are planted in rows with certain spacing, many existing methods extract crop rows according to the linear distribution of crop plants, based on which crops can be effectively separated from inter-row weeds, such as the methods described in [?, ?]. Hough transform, least square method, and pixel-histogram-based methods are the most commonly used approaches for crop row detection. Different crop row detection methods have been comprehensively listed in [?]. In addition, the plant spacing of transplanted crops is relatively fixed within crop rows, making the distribution of crops present certain patterns. Usually, researchers combine location features with shape, color, and texture features to effectively separate irregularly distributed weeds from neatly planted crops.

Southall et al. [?] adopted an extended Kalman filter approach for their crop recognition method, where a model consisting of a grid matching the crop planting pattern is incorporated. A clustering method collects plant features extracted from near-infrared field images into groups representing individual plants, followed by a crop/weed discrimination procedure based on the assumption that features not matching the planting pattern represent weeds. Hu et al. [?] proposed a crop recognition and localization approach taking advantage of knowledge about the planting pattern. The method recognizes crop plants by filtering candidate crop regions extracted from the pixel histogram of each crop row with a sinusoid curve designed according to crop spacing. Based on the fact that most crops are planted in rows with similar spacing along the row, Lottes et al. [?] established a probabilistic model representing the arrangement of plants and employed a Bayesian approach to perform crop/weed classification based on that model. They claimed that their method achieved high classification performance requiring only minimal training data and could be easily adapted to new fields.

Spatial arrangement of plants can be a reliable feature as it is much less affected by changes in visual appearance. However, it needs to be tuned for each field according to the crop planting pattern and suffers from disturbances caused by missing plants and inaccurate planting.

F. Deep-Learning-Based Crop/Weed Discrimination

Because of the wide variety of crop and weed species and the lack of a general feature, most methods discriminate crops and weeds by combining multiple features. For different recognition targets and environments, selecting appropriate features and classification methods is key to improving algorithm robustness. Deep learning technology has greatly changed the feature selection and classification manner compared with traditional methods. Deep convolutional neural networks (CNN) present strong feature extraction abilities and can perform end-to-end prediction. The application of deep learning technology in crop and weed recognition has become a new research frontier.

Dyrmann et al. [?] proposed a plant species identification algorithm based on a CNN to classify images containing 22 weed and crop species at early growth stages. These images come from six datasets with variations in illumination, resolution, and soil type. Experimental results show that the method achieved a classification accuracy of 86.2%. Potena et al. [?] designed a CNN-based method to perform crop/weed detection and classification tasks in real-time. Two CNNs were exploited in this method: a lightweight CNN was used to perform fast and robust pixel-wise vegetation detection, and a deeper CNN was then used to classify the extracted pixels into different plant species. Sun et al. [?] adopted the Faster-RCNN [?] model for broccoli plant detection in fields with different light intensities, ground moisture contents, and weed infestation levels. Through optimization of the feature extraction network and model hyperparameters, they reported an accuracy of 91.73%. Wendel et al. [?] presented a self-supervised crop/weed discrimination method that automatically leverages prior knowledge of seeding patterns to form a self-supervised classification framework resistant to variation. It achieved performance approaching that of hand-labeled training data while requiring no manual labeling. Hall et al. [?] developed a rapidly deployable weed classification system with a three-stage pipeline consisting of initial field surveillance, online processing, and data labeling. They used a CNN for plant feature extraction and another CNN for weed classification. They demonstrated that the proposed system was able to label 12.3 and 23.3 times fewer samples than traditional full data labeling, without any prior knowledge of weed species before deployment. Milioto et al. [?] proposed a pixel-wise crop/weed discrimination method based on a fully convolutional neural network (FCN) that combines several vegetation indices and preprocessing mappings to RGB images. Experimental results showed the method performed well on different test datasets despite heavy overlap between crops and weeds, and operated at around 20 Hz. Very recently, Lottes et al. [?] proposed an approach that performs pixel-wise semantic segmentation of images into soil, crop, and weed based on an FCN, encoding the spatial arrangement of plants in a row using 3D convolutions over an image sequence. Li et al. [?] devised a novel crop recognition method for high-weed-pressure scenes, inspired by the visual attention mechanism of human eyes. They constructed an FCN-based salient object detection model for pixel-wise crop/background segmentation and employed

Adaptive Affinity Fields to improve segmentation accuracy at boundaries and for fine structures. The method achieved high accuracy as well as good efficiency for real-time processing.

Recent investigations have shown that deep learning methods have significantly outperformed traditional methods that rely on hand-crafted features. They also present good generalization ability, which is an important characteristic for working in real agricultural environments since plant species and appearance change with fields and phenology. However, the vast majority of deep-learning-based methods use supervised learning, which requires large amounts of training data to obtain the best performance.

G. Available Datasets

Currently, very few open-source field image datasets are available. This is mainly due to the diversity of plant species and field conditions, and because the labeling process for field images is challenging and extremely time-consuming.

One widely used publicly available field image dataset was created by Chebrolet al. [?]. The dataset contains 5 TB of data collected by sensors equipped on an agricultural robot, including a 4-channel multispectral camera, an RGB-D sensor, and other sensors, from a sugar beet field over three months. Li et al. [?] built a field image dataset called CWF-788, which contains 788 cauliflower images captured from fields with very high weed pressure. Pixel-wise annotated ground truth labels are also provided, and the dataset is publicly available. However, the limitation of this dataset is that the number of images is relatively small, and it only contains one crop type. At present, there is still a lack of large-scale, high-quality, multi-species, open-source field image datasets for training deep plant recognition models, conducting fair comparisons, and promoting technical progress in this research area.

IV. Discussion

Controlled, stable lighting conditions can eliminate intensity and spectral changes caused by variable illumination and partial shadows. Physical solutions for dealing with variable natural light are much more direct, reliable, and easier to implement than software solutions. Although numerous research works have been done to improve algorithm robustness against changing light, the authors are inclined to design proper physical structures that can block out natural light at a sufficient level while keeping systems compact. We regard this as a necessary measure to ensure commercial weeding robots work stably and reliably in real agricultural production conditions.

Regarding the crop/weed discrimination task, the advantages of deep-learning-based methods are obvious in terms of accuracy and generalization, but the majority of them share the need for tedious labeling effort to train deep neural networks. Traditional methods still hold some advantages in computational cost, number of hyperparameters, and ease of training, as they are designed according

to prior knowledge from human experts. A comparison between traditional methods and deep-learning-based methods is depicted in [Figure 2: see original paper]. As seen in some recently reported methods [?, ?], researchers are making efforts to leverage hand-crafted features and prior knowledge in deep learning models, which helps reduce the amount of data required for training and re-tuning CNN models. Furthermore, unsupervised learning and transfer learning are also useful techniques to reduce labeling effort for training CNN models.

With rapid development in hardware technologies, cameras—including 2D, stereo, and multispectral cameras—and computing platforms are available with better performance and lower prices. Stereo vision and multispectral information can be considered more extensively. The authors strongly recommend employing stereo vision systems for crop and weed recognition tasks. The depth information provided by stereo vision systems can not only help perform object-wise crop/weed classification but also contribute to dealing with leaf occlusion and stem detection, which are challenging but important tasks for accurate plant detection and localization. CNN models such as PointNet [?] can be used to process point clouds to realize end-to-end point-wise crop/weed classification and precise localization.

For plant detection systems to meet practical application requirements, precision and efficiency are the two main criteria. Based on our survey of literature and consultation with a commercial technology supplier and farmers, an object-wise plant recognition accuracy of over 95% would be widely accepted in most cases. The requirement for pixel-wise segmentation can be somewhat lower, for example 90%, since a plant can be correctly recognized when most of its pixels are correctly identified. Regarding efficiency, the requirement is heavily dependent on the working characteristics of specific robotic weeding systems. However, an efficiency of 25 f/s would be suitable for most weeding systems, as cameras usually work with a continuous acquisition framerate of 30 f/s or 25 f/s according to the NTSC video system (30 f/s) and PAL video system (25 f/s). However, this should be achieved on the computer equipped on the weeding system, which usually has constrained computational resources.

Weed control is comprehensive and persistent work, not limited to a single weed species or a single year. Acquisition, uploading, and sharing data are requirements and trends of technology development. Previous works mainly focused on performing plant recognition and localization locally. In the future, with the promotion and application of 5G communication technologies, identification of crops and weeds can become more accurate and fine-grained with the support of online databases and computing resources. Once information about weed species, density, and distribution is obtained and uploaded, precise regional weed maps can be built, providing the basis for developing regional weed control guides.

V. Conclusion

This paper has summarized and reviewed the development of machine vision technologies applied in plant detection for robotic weeding and discussed prospects for future development. Two main challenges in plant detection tasks are first identified, followed by a detailed review of methods for addressing these challenges. It can be concluded that: 1) numerous physical solutions and algorithms have been proposed to cope with changeable natural light in field environments, while physical solutions are thought to be more reliable and easier to implement; 2) although deep-learning-based methods have outperformed traditional hand-crafted feature methods, combining hand-crafted features and other prior knowledge with deep learning models is promising for reducing labeling efforts required for training and re-tuning models; and 3) stereo and multispectral cameras can be incorporated into more systems as they provide more information and help improve accuracy and robustness in challenging conditions. We anticipate that in the future, with support from online big data and computing resources, plant recognition will become more accurate and fine-grained based on advances in artificial intelligence and communication technologies.

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