A Review on Crop and Weed Segmentation Based on Digital Images

D. Ashok Kumar and P. Prema

Abstract Apparently weed is a major menace in crop production as it competes with crops for nutrients, moisture, space and light which resulting in poor growth and development of the crop and finally yield. Yield loss accounts for even more than 70 % when crops grown under unweeded condition with severe weed infestation. There are several weed control measures being practiced in crop production, they are physical, mechanical, biological and chemical methods. Weed Management plays vital role in agriculture and horticulture production and economic benefits derived by agricultural industry. Weed is controlled mainly by application of herbicides. Weeds are not uniformly distributed in the crop and uncropped fields and mostly they are found in patches. With the help of Color and growth parameters, the weeds and crops may not be distinguished in the fields for the reasons of imbalance in availability of nutrients, water and other environmental resources. Weed control need to be done at the early stage of the crop growth. The management of weeds with in the field is imperative. Weed management practices using chemical tools propose to apply herbicide in the dosage strictly necessary based on weed infestation and location or position. Currently research is carried out relating to identification of weed spices and the location of the weed occurrence with the aims to allow accurate weeding and apply herbicides based on the weed density. Machine vision system, remote sensing and aerial imaging techniques are used for control weeds. Sensor attached electromagnetic system, imaging spectra radiometer and spectrometer can also be used to identify weeds for effective weed control. Almost all the existing weed detection methods process the captured image by segmentation of vegetation against background (soil), detection of weed vegetation pixels. Further, classification of feature extraction of

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weeds is done by color, shape and texture. The various methods studied and concepts used for crop and weed discrimination by the various researchers are discussed in this paper.

Keywords Digital image segmentation · Crop and weed · Weed detection · Feature extraction

1 Introduction

Image segmentation in general is defined as a process of partitioning an image into homogenous groups such that each region is homogenous but the union of no two adjacent regions is homogenous. Efficient image segmentation is one of the most critical tasks in automatic image processing [1]. Image segmentation has been interpreted differently for different applications. In agriculture, computer machine system were used for automatic identification of crop and weed, disease and pest. The motivation for this work is to discover the effective and efficient weed discrimination method for site specific herbicide application. This paper organized as image segmentation techniques and limits its analysis to crop and weed image segmentation.

In agriculture, researchers and farmers have recognized that weed compete with crop for water, sunlight, nutrients and space. Controlling of weed is a critical farm operation and can significantly affect the crop yield. Herbicides applications have vital importance in weed control and high crop yield. Weeds are not uniformly distributed in the field, they clumped together in patches [2] herbicides are applied with the same dose to the whole field, representing significant portion of the variable cost of agricultural production. In these days, there is a clear tendency of reducing the use of chemical agents in agricultural cultivations. The main goals of computer vision techniques developed towards this objective try to obtain products of a better quality and the saving of costs related to the crop field treatments. This tendency has been established over the recent years among various countries, creating a growing interest. The development of computer vision capabilities allows a reliable and fast identification and classification of weeds [3]. Automatic systems nowadays provide techniques to easily process the crop fields to obtain the necessary data to classify and to distinguish the crop from the weeds [4]. The developments of these systems are mainly based on the computation of geometrical characteristics of the weeds (shape factor, aspect ratio, length/ratio, etc.) [5]. Machine vision system to analyse the weed image based on the digital image captured by the imaging device and process the extracted information for decision-making to identify weed and crop and then apply the herbicide in the selected position [6]. Thus the image recognition task is important for crop and weed segmentation. Research work in this area is difficult to classify and compare due to the variations among different crop and weed species and to the different approaches taken to collect field data.

Almost all existing weed detection methods process the image based on the following steps [7] such as segmentation of vegetation against the background (soil and/or harvest residues), Detection of the vegetation pixels that represent weeds and feature extraction and classification. Efficient and automatic segmentation of vegetation from images of the ground is an important step for many applications such as weed detection for site specific treatment. With the numerous recent developments of new segmentation methodologies, the requirement of their categorizations based on successful applications have become essential for real time precision herbicide applicator. This paper contains categories the color space, image segmentation method and review of crop and weed segmentation.

2 Color Space

A color space is defined as a means by which the specification, creation and visualization of colors is performed. Color is perceived by humans as a combination of tristimulus R(red), G(green) and B(blue) which are usually called three primary color. From R,G,B representation, we can derive other kinds of color representation (spaces) by using either linear or nonlinear transformation. Several color spaces, such as RGB, Normalized RGB, HSI, CIE XYZ, CIE YUV, CIE L*a*b*, YCbCr, HSV are utilized for color image segmentation, but none of them can dominate the others for all kinds of color image. Selecting the best color space still is one of the difficulties in color image processing [8]. HSL (Hue Saturation and Lightness) represents a wealth of similar colour spaces, alternative names include HIS (intensity), HSV (value), HCI (chroma/colourfulness), HVC, HSD (hue saturation and darkness) etc. The separation of the luminance component from chrominance (colour) information is stated to have advantages in applications such as image processing. The YCbCr colour spaces separate RGB into luminance and chrominance information and are useful in compression applications (both digital and analogue). The CIE space of visible color is expressed in several common forms: CIE xyz, CIE L*a*b*, and CIE Lu'v'. CIE xyz is based on a direct graph of the signals from each of the three types of color sensors in the human eye. These are also referred to as the X, Y and Z tristimulus functions. CIE Lu'v' was created to correct for the CIE xyz distortion by distributing colors roughly proportional to their perceived color difference. A region that is twice as large in u'v' will therefore also appear to have twice the color diversity making it far more useful for visualizing and comparing different color spaces. CIE L*a*b* remaps the visible colors so that they extend equally on two axes conveniently filling a square. Each axis in the L*a*b* color space also represents an easily recognizable property of color, such as the red-green and blue-yellow shifts. These traits make L*a*b* as useful color space for editing digital images. However, almost all existing weed detection methods process the image in two steps: (1) segmentation of vegetation against the background (soil and/or harvest residues) and (2) detection of the vegetation pixels that represent weeds. The procedures for the segmentation of vegetation usually assume that all pixels belonging to vegetation can be easily extracted by some combination of the color planes on the RGB model [9]. HSI color model resolve the problem of under segmentation [10]. Other approaches propose the use of the HIS color model combined with classification methods such as Bayes networks and clustering [11]. To discriminate vegetation pixels, a linear combination of the RGB planes with coefficients ($r = -0.884$, $g = 1.262$, $b = -0.311$) and mean pixel intensity thresholding approaches were used. Extract the greenness by combining Normalized RGB indices computation methods such as ExG, CIVE, ExGR and VEG based on the uniformity of the corresponding histograms [12]. Offset excess green (OEG) combined with Non Green Subtraction (NGS) algorithm address the over segmentation problem and accurately segment vegetation under different illumination condition [13].

3 Image Segmentation

Computer vision is a rapidly expanding area that is dependent on the capability to automatically segment, classify and interpret images. Segmentation is central to the successful extraction of image features and their subsequent classification. Image segmentation techniques can be grouped into six categories [14] amplitude thresholding, component labeling, boundary based segmentation, region based segmentation, template matching and texture segmentation. During segmentation, an image is preprocessed, which can involve restoration, enhancement, or simply representation of the data [8]. Certain features are extracted to segment the image into its key components. The segmented image is routed to a classifier or an image-understanding system. The image classification process maps different regions or segments. Each object is identified by a label. The image understanding system then determines the relationships between different objects in a scene to provide a complete scene description. This session discusses the categorization of image segmentation algorithms.

Amplitude thresholding, or window slicing, is useful whenever an object is sufficiently characterized by the amplitude features. Component labelling is a simple and effective method of segmenting binary images by examining the connectivity of pixels with their neighbours and then labelling the connected sets. Boundary extraction techniques segment objects on the basis of their profiles. Therefore, such techniques as contour following, connectivity, edge linking, graph searching, curve fitting, Hough transform, and others are applicable to image segmentation. Region-based segmentation techniques are primarily used to identify various regions with similar features in one image. Region-based approaches [15] are generally less sensitive to noise than the boundary based methods. Many region based segmentation techniques are available, including region-growing and merging, relaxation labelling, symmetric nearest neighbor, hierarchical segmentation, and shadow boundary segmentation, several well-known image processing techniques are offered in the context of region-based segmentation, such as clustering, pattern recognition, edge-detection, noise reduction, and three-dimensional object recognition. Clustering refers to a class of algorithms used extensively for image segmentation. Clustering assembles unlabelled data by sets. Data point values represent characteristic features of interest such as grayscale, color brightness, contrast etc. During the cluster operation, the clusters are assigned labels that arc mapped back into the image, so that the original pixel values are replaced. The basic clustering operation examines each pixel individually and assigns it to the cluster that best represents the value of its characteristic vector. This assignment is done according to the selected measure of similarity between the data point and the criterion function that measures clustering quality. The process is repeated until some condition is satisfied by the current grouping of data points. Texture segmentation becomes important when objects in a scene have a textured background [16]. Since texture often contains a high density of edges. Clustering and region-based approaches applied to textured features can be used to segment textured regions. In general, texture segmentation and classification is a complicated problem. Use of a priori knowledge about the existence and kinds of textures that may be present in a scene can be beneficial when applied to practical problems.

4 Categorisation Based on Homogeneity Measure

Next stage of categorization corresponds to the homogeneity measures used for image segmentation. The primary homogeneity measure is spectral/tonal feature. Secondary homogeneity measures are spatial, texture, shape and size. Tertiary homogeneity measures are contextual, temporal and prior knowledge [17]. The most primitive measures of homogeneity are spectral and textural features. Texture features points to spatial pattern represented by spectral values [18]. A textured image may have various texture patterns. However, quantitatively characterizing texture is not simple [17]. Due to this fact texture segmentation has been studied widely in combination with other features like shape, spectral and contextual and various models till today. Texture segmentation is mostly used after segmentation technique. This is mainly because of the presence of highly textured regions in high resolution satellite imagery. Currently, the research has shifted from texture to multiresolution model. The importance of shape and size measure could be understood when the natural object are to be identified. The state of art use of shape and size refers to multi-scale/multiresolution approach to image segmentation. Shape and size measures are especially helpful when delineating complex objects in high resolution satellite imagery. Prior knowledge refers to photo interpreter knowledge regarding the regions/objects of the image [17]. It may be the knowledge of classes of the image region or about some specific area, building or trends etc. Incorporating prior knowledge in image analysis is one steps towards developing artificial intelligence in the machine [19]. Prior knowledge is specifically useful when for segmentation of complex landscape object indistinguishable using texture and context.

5 Literature Review for Crop and Weed Segmentation

In computer vision, segmentation is a process by which an image is partitioned into multiple regions (pixel clusters). The aim of segmentation is to obtain a new image in which it is easy to detect regions of interest, localize objects, or determine characteristic features such as edges. The image obtained by the segmentation process is a collection of disjoint regions covering the entire image whereby all the pixels of a particular region share some characteristic such as color, intensity, or texture. Lists of models generally used for image segmentation are Object Background/Threshold Model, Neural Model, Fuzzy Model, Multi-resolution and Wavelet model.

5.1 Thresholding and Neural Network Based Approaches

Artificial Neural Networks (ANN) are widely applied for pattern recognition. Their extended parallel processing capability and nonlinear characteristics are used for classification and clustering. In crop and weed discrimination, the acquired input image are preprocessed using filters. The processed color images were converted into grey level images and later binary images were created for easier identification of weed [5]. Image segmentation was initially focused to detect weed seedlings based on geometrical measurements such as shape factor, aspect ratio, and length/area [5, 20]. In traditional plant taxonomies plants are identified based on shape features, colour, texture, etc. Although there are methods to identify individual shapes, the major challenge is to separate one green leaf from another green leaf. It becomes more difficult when two different shaped leaves overlap.In crop and weed detection, problem also arises when individual leaves have similar boundary characteristics and it becomes difficult to define and perform subsequent shape analysis. Various studies conducted on image based identification of weed and various classification features are listed in Table 1. Colour images were successfully used to detect weeds, seeds and other types of pests [21].

To identify and detect weeds and crop plants under uncontrolled outdoor illuminations condition normalized excessive green conversion, statistical threshold value estimation, adaptive image segmentation, median filter was applied to segmented images to eliminate random noise. Morphological features of plants and Artificial Neural Network (ANN) techniques are used for better classification [20]. RGB planes with coefficients ($r = -0.884$, $g = 1.262$, $b = -0.311$) and mean pixel intensity thresholding and Robust Crop Row Detection system [22] successfully detects an average of 95 % of weeds and 80 % of crops under different

Table 1 Studies on vegetation detection using imaging techniques

Crop/weed	Features			Statistical methods	Reference
	Shape	Color	Texture		
Blueberry and weed	–	Excess green	–	Statistical and spatial frequency Hough transform	Fangming et.al. [38]
Crop and weed	Height	Excess green	Wavelet statistical features, second-order statistical features	Multi resolution combined statistical and spatial frequency	Sabeenian and Palanisamy [34]
Barley and wild oat		RGB Planes with coefficient(r=-0.884, g=1.262,b=-0.311)	–	Mean percentage of crop an weed pixels	Xavier et al. [22]
Canola and narrow leaf weed	Area, Perimeter, eccentricity, circularity	Excess green	Radial spectral energy	Fourier and Bayesian classifier	Mathanker et al. [37]
Cabbage, carrot and weed	Area, eccentricity, convexity, roundness	Hue, saturation, intensity	–	Fuzzy logic	Hemming and Rath [11]

illumination, soil humidity and weed/crop growth conditions. For the effective classification of crops and weeds in digital images [5] Otsu thresholding, morphological methods and feature space as colour features, size dependent object descriptors, size independent shape features and moment invariants are used in support vector machine (SVM).

Weed species retard the growth of the crop and reduce farm yields. To control the growth of weed species, a large number of herbicides are used in agriculture fields. Discrimination between corn seedlings and weeds is an important and necessary step to implement spatially variable herbicides application [23]. Otsu's threshold was applied to segment weeds images based on the modified excess green feature, it could distinguish the plant objects from the background effectively. The probabilistic neural network classifier was created for recognition of corn seedlings and weeds according to the shape features. Comparing the probabilistic neural network (PNN) method with the back propagation neural network, the BP method is better than the PNN seeing from the experimental results.

Weeds are general green color, a highly irregular leaf shape and varying surface texture, and an open plant structure which contributes to its being a challenging task to identify weeds in the field [24]. The Anisotropic Diffusion Based Weed Classifier is based on anisotropic diffusion also called Perona-Malik diffusion. This classifier classifies the images in four categories i.e. Broad Leaf, Narrow Leaf, Low Weed and Mixed. The Anisotropic diffusion enhance the image by considering the local structures in the images to filter noise, preserve edges and significantly increasing the signal-to noise ratio (SNR) with no major quantitative distortions of the signal. Since information about weed numbers in unit area and average weed size (age) could be used to make the decision to skip some low weed density control zones or to decide between multiple application rates for different weed infestation levels. This algorithm give is 95 % accuracy in classification of different leaf textures.

Several methods have been implemented for accurate weed detection: spectral reflectance of plants with artificial neural networks [25], or statistical analysis [6, 26] such as Principal Component Analysis. Gray Level Co-occurrence Matrix (GLCM) [27], statistical properties of the histogram, texture features and Support Vector Machine (SVM). Other researchers have investigated texture features [28] or biological morphology such as leaf shape recognition [27]. However, for use in real-time, there have been fast methods are implemented to identify crop rows in images [29]. Most are based on Hough transform [30, 31], Kalman filtering [32] and linear regression [21]. Moreover, Hough transform is usually implemented for automatic guidance in crop fields [33]. Consequently, there are now various vision systems available on autonomous weed control robots for mechanical weed removal.

5.2 Wavelet Based Approach

Wavelet transform is the best trade-off to represent both time and frequency content of a signal. There are a number of ways to separate the low (smooth variations in colour) and the high frequency components (the edges which give details). One way is decomposition of the image using the discrete dyadic wavelet transform. A multiresolution analysis (MRA) based on the well known Mallat algorithm gives image details at various scales. With MRA and separable wavelet basis functions, we can extract the details contained in various parts of the image from different levels of resolution. A new method based on Gabor wavelets (GW), Lie group structure of region covariance (LRC) representation and texture characteristics of the weed image at different directions and scales was applied for classification of broadleaf weed images on Riemannian manifolds [15]. Multi-resolution Combined Statistical and Spatial Frequency (MRCSF) and texture features [34] are used to classify weed images as broad and narrow weed. Bossu et al. [35] tested and validating the accuracy of four wavelet algorithms (Daubechies 25, Symlet, Coiflet, Biorthogonal, Reverse Biorthogonal Meyer) for crop/weed discrimination in synthetic and real images. The accuracy of these algorithms for different Weed Infestation Rates (WIR) was compared to Gabor filtering, which is currently implemented for real-time site-specific sprayer from vision system [36]. The best results were with Daubechies and discrete approximation Meyer wavelets. They provided better results than Gabor filtering not only for crop/weed classification but also in processing time.

The crop and weed segmentation techniques are summarized in Table 2 based on the above literature. The literature has revealed that researchers have followed many different ways for weed detection and decision-making but the most common steps include image acquisition. After acquiring an image, it is processed for band separation, or an excess green image is generated and removing blobs, holes, shades, etc. from the image. The processed image is then converted into binary image using threshold. Various methods of such thresholding have been utilised by different researchers. Based upon threshold values regions of similar values is segmented and each segment is treated as a region of interest (ROI). Once the ROI is defined, various geometrical measurements are obtained such as height, length, minimum bounding rectangle, major and minor axis, perimeter, area, textural parameter such as energy, entropy, contrast, moments, etc. These features can be distinctive to a particular species of crop or weed and can be utilised for differentiating between two species of the crops or crop and weed. These features could also be utilised for further analysis.

Table 2 Crop and weed segmentation techniques

Crop	Color space	Segmentation techniques	Features	Classification method	Reference
Corn and weed images	Excessive green	Adaptive image segmentation	Morphological features	Artificial neural network	Hong et al. [20]
Maize	RGB planes with coefficients	Fast image processing, robust crop row detection	Mean	support vector machine (SVM), Bayesian classifier	Xavier et al. [22]
Chilli, pigweed	Excessive green	Global thresholding	Colour features, size dependent object descriptors, size independent shape features and moment invariants	Support vector machine	Ahmed [5]
Cereals	RGB	Thresholding and hough transform lines detection	Shape and size features	Support vector machine	Tellaechea [3]
Cotton	Excessive green	Thresholding	Size, shape features	Statistics of time-consuming	Yin Donu 2011
Paddy sugarcane, sunflower, onion and tomato	Excessive green	Wavelet based MRCS and spatial frequency	Texture features	Statistics features	Sabeenian and Palanisamy [34]
Corn	Excessive green	Gray level co-occurrence matrix	Texture features	Support vector machine, back-propagation (BP) neural network	Wu [27]
Crop and weed	Excessive green	Wavelet daubechies 25, symlet, coiflet, biorthogonal reverse	Color	Confusion matrix	Bossu [35]
Corn	Excess green	Color segmentation and thresholding	Shape features	Probabilistic neural networks	Chen [23]

6 Conclusion and Future Work

It could be concluded from the above study that various color space methods are used for foreground and background extraction. With the numerous amounts of crop and weed segmentation techniques presented above. The color space RGB planes with coefficients ($r = -0.884$, $g = 1.262$, $b = -0.311$), mean pixel intensity thresholding and Robust Crop Row Detection system successfully detects an average of 95 % of weeds and 80 % of crops under different illumination, soil humidity and weed/crop growth conditions. For real time precision herbicide application, Offset excess green and Non-Green Subtraction algorithm address the over segmentation problem. This method is detect weeds under different lighting conditions and it is suitable for using in real-time application. Other vegetative methods HSI, YCbCr methods, thresholding techniques, median filter, morphological operation are used for vegetative segmentation. Homogeneity measures are spectral, spatial, texture, shape, size, contextual, temporal and prior knowledge used for crop and weed feature extraction. The widely applied homogeneity measure is based on color and texture. Wavelet segmentation algorithm is currently used crop and weed discrimination. Wavelet and texture segmentation is more successful because it inherits spectral and spatial properties in itself. The selection of segmentation approach depends on what quality of segmentation is required. Further, it also depends on what scale of information is required. For qualitative and quantitative comparison confusion matrix, discriminate analysis, neural network, Bayesian classifier and support machine vector are used. For classification of crop and weed neural network approach gives good result. Having gone through the techniques above, still it need further improvement for effective method of weed segmentation, it could be achieved by involving hybrid techniques (a combination of two or more of the segmentation techniques) in future course of work.

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