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An overview on crop-weed discrimination based on digital image processing using textural features

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Abstract
Weed control is a serious issue for maximizing the yield. The traditional weed management approaches are less effective, and requires high labor force in peak seasons. Modern machineries using site-specific weed management (SSWM) system manages weed precisely and delivered a precise amount of chemicals to only weeds. The heart of the SSWM system is a digital image processing system that involves image preprocessing, vegetation segmentation, feature extraction, and classification. The feature extracted from the images using color, spectral and spatial method had several limitations concerning color; inter-row spacing and crop-weed growth at different stages. The texture-based feature extraction process for image classification is the best possible way over others. It involves statistical GLCM matrix, structure, wavelet, and Model-based textural features. Statistical and wavelet based textural features are most commonly used for crop-weed classification system. The texture features can recognize weed with more than 90% accuracy and are more effective than other feature extraction methods. Therefore, it had huge potential and scope in SSWM machinery.

Keywords: Digital image processing, texture, SSWM, GLCM, weed management

Introduction
India's population is increasing at a tremendous rate of 1.2% every year. It proportionally demands more production in agriculture for their survival**.** Weed is one important factor affects crop yield significantly. Hodgson, 1968 [13] reported wheat yield loss by 15% and cotton by 60% (Keeley and Thullen, 1989) [14, 15] due to weeds presence in the field. There are various methods i.e. manual, mechanical and chemical for controlling the weeds. Manual methods like in-roe hand hoeing are energy-intensive, demands more labors and cost. Mechanical methods i.e. intercultural equipment's cultivators, spring and spike tooth harrow are not suitable for intra row weeding. Chemicals methods are most commonly used in Indian conditions i.e. knapsack sprayers, animal-drawn sprayers, and tractor-mounted boom sprayers. These involve applying chemicals to the entire field which nowadays due to excessive use polluting soil, contaminating ground, surface water and also polluting the environment (Savci, 2012) [27, 28]. One alternative approach recently developed is Site-Specific Weed Management (SSWM). It involves the application of chemicals to only weed patches. It consists of a system mounted on off-road vehicles that sense the weed-crop field data, process it and actuate the applicator mechanism. Sensing techniques are broadly classified into two categories airborne remote sensing and ground-based remote sensing. Airborne remote sensing i.e. the unmanned aerial vehicle, a sensor mounted on balloons and satellite-based has lower spatial resolution and are suitable for larger areas. Ground-based sensing techniques such as optical and spectrometers can sense the field data in real-time and their spatial resolution are higher. Optical imaging allows capturing/acquisition of image data, processes it through computers or microprocessors for crop-weed discrimination and facilitates the spraying mechanism to apply chemicals to only weeds. Digital image processing with suitable application technology has the potential to reduce chemical consumption by 50% without affecting the crop. Digital Image processing is considered as the heart of this system which processes field images consisting of the crop, weed, and soil and classifies it. This review article will provide a basic overview of digital image preprocessing and emphasize on textural based approach for crop weed discrimination.

This review paper is divided into 4 sections. Section.1 gives a brief idea about the basic components in digital-image processing system. Section.2 gives a detailed overview of the procedure of weed–crop discrimination. While section.3 emphasizes textural based features for the discrimination process. Section.4 concludes the study.

Section 1: General components and working of Digital image processing systems

The system consists of an image sensor i.e. cameras (RGB camera, an infrared camera, multi-spectra or hyper-spectral camera, etc.), input devices, computer (microprocessor), image processing software and output device. The image sensor captures and acquired the field data which transfers to the computer (micro-processor) through input devices; the image processing software within the computer process the field images consisting of crop, weed, and soil and classify them based on features. The image processing software's used algorithm to distinguish crop from weed.

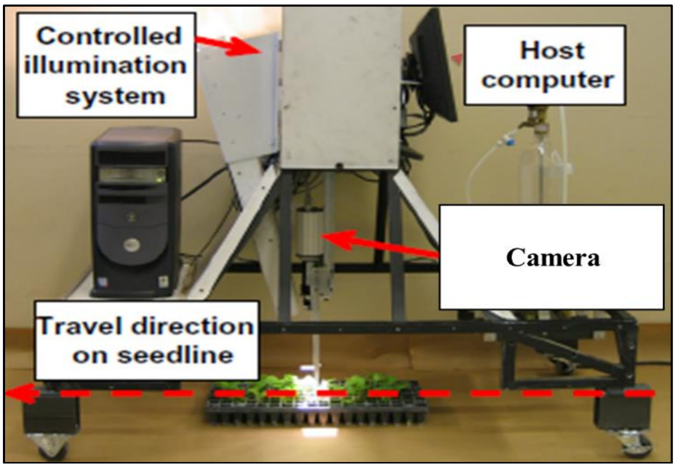

Fig 1: Components of Digital image processing systems (Zhang *et al*., 2012) [30].

Section 2: Overview of image processing-based crop-weed discrimination process

A general image processing procedure (Fig. 2) includes pre-processing and enhancement for image modification, vegetation segmentation for removing vegetation against background, feature extraction for differentiating crop-weed and final classification for labeling crop and weed (Chitradevi B, Srimathi P. 2014) [5].

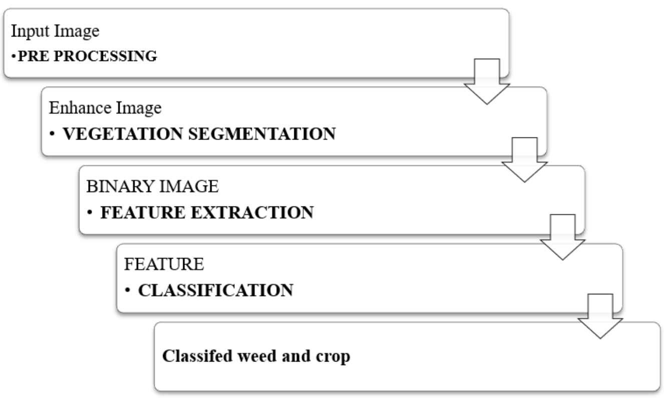

Fig 2: Flowc hart of crop-weed discrimination process (Source - Chitradevi B. and Srimathi P., 2014) [5].

Image preprocessing

Pre-processing of an image improves and enhanced image quality by removing the noise, modifying features and resizing the image. It facilitates the vegetation segmentation process. It includes transformation in color space, resizing, contrast enhancement, normalization and de-noising, etc.

Vegetation segmentation

It is the process of separation of vegetation (crop-weed) from the background soil or grouping of related pixels together. Effective features must be used to differentiate between plants and soil, this pertains efficient segmentation. Normalized Difference Index (*NDI*), Green chromaticity and Excess Green Index (*ExG*) are some color-based indices. These are all separates the green part from a dark background. Final Separation was done using: threshold-based approach. In threshold-based segmentation image converted to grayscale and intensity values of each is compared with the pre-set threshold values, and then similar pixels are grouped into corresponding classes according to the comparison results. Meyer *et al*., 1999 [21] distinguished soil or residue-based living plants of two grass species (Shatter cane, Green Foxtail) and two broadleaf species (Velvetleaf, Red Root Pigweed) using an excess green index method. Deemed *et al*., 2018 [8] also used excessive green index for soil-vegetation segmentation. Haug *et al*., 2014 [12] used spectral based Normalized Difference Vegetation Index (NDVI) index for removing background soil against biomass by considering the visible red and near-infrared light. In the input images, they have applied the NDVI to each pixel pair. The difference between red (R) and green (G) color components were used for removing green regions (sugar beet plants and weeds) from the background soil using optimum threshold based on Otsu technique (Bakshipur *et al*., 2017) [2]. Table 1 listed out some color based index used by researcher for segmentation of soil and green regions. The result obtained from vegetation segmentation i.e. the green region (crop-weed) goes as an input to the feature extraction process.

Table 1: Color based index and their formulas.

Index	Formulas	References
Normalized r,g	R =R/(R+G+B), g=G/(R+G+B),	Yang *et al.*, 2000
Excess green index	ExGeExR = ExG-(1.4×R-G) ExGR= ExG-(1.4r-g)	Meyer *et al*., 1999 [21].
NDVI	NDVI=NIR-R/(NIR+IR	Haug *et al*., 2014 [12]
Otsu algorithm	$\sigma_w^2(t) = w_0(t)\sigma_0{}^2(t) + w_1(t)\sigma_1{}^2(t)$ Where w_0 and w_1 are the probabilities of two classes while σ_0 and σ_1 are the variances of two classes.	Bakshipur *et al*., 2017 [2].

Feature extraction

It is the most important step in digital image processing. Weed can be distinguished from the crop by using four features: biological morphology, spectral features, visual textures, and spatial contexts. Biological morphology is related to the size, shape, and structure of the plant or any of its parts. The shape factors and shape indices for segmented regions are different for crop and weed which can be used for discriminating them. But as the crop stage progress, the morphological characteristics changes and induce high complexity in the discrimination process**.** Spectral features are applied to the image having a crop with a different color from weeds. The crop-weed can be segmented using spectral features such as Normalized Difference vegetation index (NDVI) (Haug *et al.*, 2014) [12] Modified Chlorophyll Absorptance Reflectance Index (MCARI) (Eddy *et al*., 2013) etc. These are not suitable for plants with a similar color to weed. Spatial contexts feature extraction is suitable for the crop that is planted in rows (wheat and barley etc.) with a prior pattern. In this, all the green plants between two adjacent crop plants are regarded as a weed. But most of the crops which are not sown in rows cannot be classified using spatial based feature extraction. Texture based features can be used for effective crop-weed discrimination**.** In general the elements representing the gray levels arrangement of pixels in a region of a digital-image are Textural features. It is a widely used technique in image processing for extracting useful information. It provides measures of properties such as coarseness, smoothness, and regularity and identifies regions of interest in an image. In the subsequent section, we will discuss primarily texture-based feature extraction in detail.

Section 3: Texture based recognition of plants

The texture is one of the most important features for recognizing patterns in an image. Image texture is related to features such as fineness, coarseness, granulation, smoothness, randomness, lineated, mottled, irregularity, or hummocky (Haralick, 1979) [11]. Texture based features broadly classified into four classes of statistical methods, structural methods, model-based methods and filtering based methods (Liu *et al*., 2004) [19]. Surface texture can be analyzed on both structural and statistical levels using computer vision (Rosenfeld and Lipkin, 1970) [26].

Statistical characteristics are derived from the statistical distribution of gray values by measuring local characteristics at each point of the object and drawing a set of statistics from the distribution of local characteristics. An intensity histogram can be an example for region or image that is obtained using statistical features like flatness, skewness, and contrast of histogram. Cheng *et al*., 2014 discriminated rice from weed using texture-based multiple features based on the histogram. The histogram analyses and extracted the central tendency and variation at each data point in the surrounding area and feed into a machine classification algorithms (Table 2).Co-occurrence matrix such as Gray label co-occurrence matrices (GLCM), the potential application of a statistical-based feature method was used by Chowdhury *et al*., 2015 [6] and Bakhshipour *et al*., 2017 [2]. GLCM analyses the changes in the brightness of pixels, preserves the spatial information and obtains statistical data (Pulido *et al.*, 2017; Tomito and Tsuji, 1990) [24, 29]. It also describes the spatial structure of local textural features in the image and indicates how often a pixel with gray-level value horizontally adjacent to a pixel is with each other. Meyer *et al*., 1999 [21] extracted four standard textural features for crop plants and soil using grayscale images i.e., second angular moment, entropy, inertia, and local homogeneity. These features were derived from the co-occurrence matrix.

Table 2: Statistical texture features based on Histogram

	Contrast of histogram	**The intensity contrast of correlation matrices**	
Textural features (Based on only Histogram)	Mean of histogram	the first moment of gray image	Cheng & Matson (2015) [4]
	Variance of histogram	The second moment of gray image	
	Skewness of histogram	The third moment of gray image	
	Flatness of histogram	The fourth moment of gray image	
	Maximum of histogram	The uniformity of gray image	
	Correlation of histogram	The correlation of gray image	
	Closeness of histogram	The homogeneity of gray image	
Histogram along with positional features	Correlation	The correlation of correlation matrices	Cheng & Matson (2015) [4]
	Uniformity	The uniformity of correlation matrices	
	Closeness	The homogeneity of correlation matrices	
	Strongest	response The maximum probability of correlation matrices	
	Contrast	The intensity contrast of gray image matrices	

Pulido *et al*., 2017 [24] discriminates vegetables crop and weeds from outdoor crop images using 10 textural features as shown in Table 3.

Table 3: Statistical textural features for crop-weed discrimination

Feature	Formulas	References
Autocorrelation	$\sum_i \sum_j (i,j)p(i,j)$	Pulido *et al.*, 2017 [24].
Contrast	$\sum_{n=0}^{N_g-1} n^2 \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \{p(i,j)\}$	Arivazhagan *et al.*, 2013; Pulido *et al.*, 2017; Lin *et al.*, 2017 [24].
Correlation	$\frac{\sum_i \sum_j (i,j)p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$	Pulido *et al.*, 2017 [24].
Energy	$\sum_i \sum_j p(i,j)^2$	Arivazhagan *et al.*, 2013; Pulido *et al*., 2017 [24].
Dissimilarity	$\sum_i \sum_j \lvert i-j \rvert * p(i,j)$	Pulido *et al*., 2017 [24].
Entropy	$-\sum_i \sum_j p(i,j) log(p(i,j))$	Pulido *et al*., 2017; Lin *et al*., 2017 [24].

Homogeneity	$\sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j)$	Arivazhagan *et al.*, 2013; Pulido *et al.*, 2017; Lin *et al.*, 2017 [24].
Variance	$\sum_i \sum_j (i-j)^2 p(i,j)$	Pulido *et al.*, 2017 [24].
Difference variance	$varinace\ of\ p_{x-y}$	Pulido *et al.*,2017 [24]
Cluster shade	$\sum_i \sum_j (i+j-\mu_x-\mu_y)^3 p(i,j)$	Arivazhagan *et al.*, 2013, Pulido *et al.*, 2017 [24].

Haug *et al.*, 2014 [12] extracted statistical texture features from NDVI images as shown in Table 4 for facilitating the classification between carrot plants and two weed classes.

Structural based textures features refer to the composition of well-defined texture elements for example regularly spaced parallel lines. Crop and weed have different structural characteristics. Structural texture features were categorized by set primitives (Texels) and placement rules. The texels represent by gray levels i.e., shape/homogeneity of some local property. While the placement rules represent the relationship between Texels (Lee 2004) [18]. The structural textural was not used in the literature related to crop weed segmentation because they can only outline coarse texture.

Table 4: Statistical texture features based on central tendency and variance

Statistical features.	**Minimum of biomass pixel intensities**	(Haug *et al*, 2014) [12]
	Maximum of biomass pixel intensities	
	Range of biomass pixel intensities	
	Mean of biomass pixel intensities	
	Median of biomass pixel intensities	
	Standard deviation of biomass pixel intensities	
	Kurtosis of biomass pixel intensities	
	Skewness of biomass pixel Ntensities	

Other types of textural features are of transformation types such as wavelet transformation. Wavelet extracts information from different spatial orientations and helps in analyzing images. This type of transformation was done using filters such as Haar, Daubechies, and Gabor which converts the original image data into a new domain and helps to identify some new features. Grigorescu *et al.*, 2002 used Gabor filter which is a linear and local filter characterized by preferred orientation and preferred spatial frequency. Haar filter is another type of filter used for the texture-based segmentation process but it is non-continuous and non- differentiable and used for analysis signals having sudden transition (Chui, C. K. (1992) [7]. Bakhshipour *et al.*, 2017 [2] discriminated pigweed, lambsquarters, hare's-ear mustard and turnip weed from sugar beet using 13 wavelet-texture based features obtained using Haar filter from GLCM (Table 5). It represents images with vertical details, horizontal details, and the diagonal details. Mallat in 1989 [20] also used transformed wavelet textural features for segmentation. Liu *et al.*, 2004 [19] used a directional empirical mode decomposition (DEMD) filter approach for texture-based segmentation. DEMD decomposes signals by shifting and analyzing the frequency. At each point, it generates 4 features that were extracted using decomposition. Unlike wavelet-based filtering, it identifies the distance between the adjacent extreme by an iterative process. It also defines directional frequency and envelops features by 2D Hilbert transform after decomposing images. The research conducted by Deemed *et al.*, 2018 [8] had used the discrete Framelet Transform (FrDWT), a statistical-based texture feature extraction process for segmenting crops from weed. This feature decomposes image signals into different multi-resolution components (Horizontal, Diagonal, Vertical) preserving the original information.

Table 5: Wavelet-texture features using from the co-occurrence matrices (Bakhshipour *et al.*, 2017) [2].

SI No.	Feature	Description	Formulae
1.	Ent	Entropy texture feature	$Ent = \sum_i^{N_g} \sum_j^{N_g} C(i,j) log C(i,j)$
2.	Enr	Energy texture feature	$Enr = \sum_i^{N_g} \sum_j^{N_g} [C(i,j)]^2$
3.	$Iner$	Inertia texture feature	$Inner = \sum_i^{N_g} \sum_j^{N_g} (i-j)^2 C(i,j)$
4.	$Corr$	Correlation texture feature	$Corr = \sum_i^{N_g} \sum_j^{N_g} \frac{(ij)C(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$
5.	IDM	Inverse Different Moment	$IDM = \sum_i^{N_g} \sum_j^{N_g} \frac{1}{1+(i-j)^2} C(i,j)$
6.	Var	Variance texture feature	$Var = \sum_i^{N_g} \sum_j^{N_g} (i-\mu)^2 C(i,j)$
7.	S_{ave}	Sum average of co-occurrence matrix	$S_{ave} = \sum_i^{2N_g} i C_{x+y}(i)$

8.	S_{var}	Sum variance of co-occurrence matrix	$S_{var} = \sum_{i=2}^{2N_g} [1 - (Sum_{Average})]^2 C_{x+y}(i)$
9.	S_{ent}	Sum entropy of co-occurrence matrix	$S_{ent} = -C_{x+y} \sum_{i=2}^{2N_g} C_{x+y}(i) \log(C_{x+y}(i))$
10.	D_{var}	variance of difference	$D_{var} = \sum_{i=0}^{2N_g} (i - \mu_{x-y})^2 C_{x-y}(i)$
11.	D_{ent}	Entropy of difference	$D_{ent} = -\sum_{i-0}^{N_g} C_{x-y}(i) \log(C_{x-y}(i))$
12.	Cl_{sh}	Cluster shade	$Cl_{sh} = \sum_{i}^{N_g} \sum_{i}^{N_g} (i - M_x + j - M_y)^3 C(i,j)$
13.	Cl_{pr}	Custer prominence	$Cl_{pr} = \sum_{i}^{N_g} \sum_{i}^{N_g} (i - M_x + j - M_y)^4 C(i,j)$
14.	$C_x(i)$	Sum of the entries in the ith row of GLCM	$C_x(i) = \sum_{j=1}^{N_g} C_{ij}$

The Model-based textural features such as fractal model and Markov model are based on image structure. They define an image based on a probability model or a linear combination of a set of basic functions. The fractal model had been used for images having natural textures with statistically quality of using different scales and self-similarity. Different types of models-based feature extraction techniques such as 1-D time-series models, Auto-Regressive (AR), Random filed models, Moving Average (MA), Markov model and Auto-Regressive Moving Average (ARMA) depending on the neighborhood system and noise sources are used. Random field models analyze spatial variations in two dimensions. While Markov models using the conditional probability of green pixel in its neighborhood. The literature cited indicates no significant work had been done using model-based texture for classification of crop-weed segmentation.

Classification result

After feature extraction from the images, several features can be merged to get a robust method. Two kinds of classification methods were commonly used threshold-based and machine learning types as discussed in the vegetation segmentation process. A threshold-based technique used a threshold value above or below which the crop and weed are categorized. Another vegetation segmentation approach is the learning-based one. The learning-based algorithm learns common properties of objects in the image by algorithms, through which pixels are classified into different categories. These are categorized under supervised and unsupervised learning algorithms. Supervised learning algorithms methods such as Multivariate-Gaussian model (Hall *et al*., 2017) [10] lightweight CNN (convolutional-neural networks) (Potena *et al*., 2017) [22] decision-tree (Gao *et al*., 2013**),** Fisher Linear Discriminant (Zheng *et al*., 2010) [31] and Support Vector Machines (Guerrero *et al*., 2012), etc. In these methods, the training and validating process was carried out and input images with annotations were supplied during training. In the training process, known input and known output were fed to the system and inherent coefficients were estimated to build the model. Hence, the classification model performs well for images with similar properties with the training samples, and its performance is dependent on the selected samples. Unsupervised learning algorithms were based on K-means clustering (Kumar and Prema, 2016; Prema and Murugan, 2016) [23, 24] and K-means clustering based on particle swarm optimization (PSO) (Bai et al., 2014) [1] spatial clustering based on density applications with noise (DBSCAN) (Cheng, B., & Matson, E. (2015) [4] etc. In this method, no image labeling is required. Cheng, B., & Matson, E. (2015) uses SVM, Decision tree and Naiver Bayes supervised algorithms for clustering of weed and rice. They found that true positive weed detection rate and precision were greater than 0.92 and 0.959for all the three supervised algorithms. The false weed detection rate was lesser than 0.066 for all which represents the acceptability of these algorithms. Pulido *et al.*, 2017 [24] recognized weed with sensitivity, specificity, and precision parameters; all were greater than 90% based on 10 textural features obtained from GLCM using PCA. Canonical and stepwise discriminant analyses were employed to examine texture classification performance and were found with classification accuracies of 93 and 85%, respectively for grass and broadleaf categories of plants (Meyer *et al*., 1999) [21]. Haug *et al*., 2014 [12] used a Random Forest classifier to approximate crop/weed protection at scattered pixel locations based on characteristics from a wide overlapping neighborhood. The application of the crop classification system to objects resulted in an overall weed classification accuracy of 93:8%. The result obtained from the study of Mallat (1989) [20] revealed that wavelet transformation increases effectiveness by 4.5% compared to existing color-based methods. Bakshipour *et al*., 2017 [2] used artificial neural networks for texture classification. Results showed that the wavelet texture function was able to distinguish weeds among the plant with an accurate 96 percent detection rate while at most 4 percent of sugar beets are incorrectly labeled as weeds. Frame let transform showed better segmentation compare with without texture features between weed and crop (Deemed *et al.*, 2018) [8].

Conclusion

Weed detection is a serious threat to controlling it. The problem needs several sources of information to be gathered for successful discrimination. Digital image processing is an effective tool for the identification of weed in field images. Textural based features for crop weed discrimination use statistical (Histogram, GLCM) and Wavelet-based feature extraction. Statistical GLCM matrix-based feature extraction obtains histogram, energy, entropy, contrast, inverse difference moment and directional moment to analysis change in brightness label. Wavelet features extracts data from different spatial orientations and helps in analyzing images by identifying new features. The structure and model based textural features were not used in crop-weed classification system because of theirs failure in handling of finer texture. The textural feature tended to achieve weed detection accuracy greater than 90% and more effectiveness 4.5% over color-based approach. SSWM machineries based on digital image processing using texture-based feature extraction could provide a huge potential for successful machine-based recognition that will help in protecting the environment by lesser application and helpful in achieving the precision agriculture objectives.

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