TEXTURE BASED WEED IDENTIFICATION SYSTEM FOR PRECISION FARMING

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Abstract

Weed control within crop fields is one of the main problems in precision farming. For centuries, different weed removal handheld tools have been used to minimize weeds in the crop fields. The automation of weed detection and removal in the agricultural field is a vital task which greatly improves the cost effectiveness and efficiency of the weed removal processes. This paper compares two texture extraction methods tailored for weed removal process. Nowadays several image processing techniques are used for the identification of weeds in crop field. Eventually it also discusses the performance of those texture extraction and feature selection methods and a classifier which classifies the crop and weed and overcomes the challenges facing in the present day research of weed removal technique in image processing.

Keywords- Image classification, Morphological operator, Leaf textures extractor, Feature selector, Classifier

I. INTRODUCTION

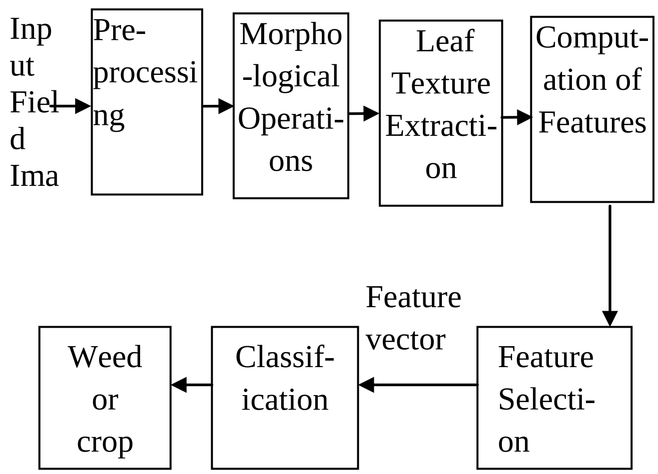
Agriculture is a major contributor to the Indian economy. In order to achieve maximum yield, the best agricultural practices must be followed. One of the most important practices is weed management. Weeds adversely affect the crop yield as they compete in acquiring plant nutrients and resources. They are also responsible for harbouring various crop pests and diseases. Weeds have very fast growth rates compared to crops, and if not treated and managed, they may dominate the field. The simple weed control method is manual weed control. But the main disadvantage in this method is that the labour required for manual weeding is expensive, time consuming and difficult to organize. Furthermore, several health issues involved with the manual labourers make manual weed control difficult to implement. Advances in computational and detection capabilities have led to the implementation of automation of agricultural practices. With automation, the weed removal process is operated autonomously which reduces human intervention and optimizes the mechanical functionalities of the machine. Automated machines also offer the choice of weed removal. This include

i) Chemical weeding
ii) Mechanical weeding

II. RELATED WORK

Typically, uniform application of herbicides is followed in the field which induces air, water and soil pollution. However, site specific application of herbicides would reduce the pollution and cost of weed control. Mechanical approaches use selective machines or add-on tools to uproot the weeds close to the crop, without damaging the crop (Weide et al., 2008). Selection of the best weed management technique for agricultural fields is governed by the factors such as geographic location, planting date, weed species present and method of irrigation. Several herbicides are registered for selective weed control (Lamm et al., 2002; Zhang et al., 2012), but no single chemical will control all weeds that infest the crops in fields. Frequently two or more herbicides may have to be combined sequentially or as tank mixes to achieve adequate broad-spectrum weed control. The weed species present to a large degree determine the choice of herbicides in such combinations. Weed control, particularly within the crop row, is a process which requires the intelligence to distinguish between crop and weed which is usually done by manual labour. The disadvantage of this method is the unreliability of labour and the high cost incurred along with it. In order to obtain the advantages of both mechanical and manual approaches, the automation technology has been applied to weed management. Colour, shape (Perez et al., 2000; Lamm et al., 2002), spectral (Zhang et al., 2012) and texture (Guijarro et al., 2011) are the predominant features used by the past literatures in this field. The following passages describe the existing methodologies used for weed identification in agricultural fields. The shape features discriminate the broad and narrow leaves. Therefore Cho et al. (2002) assessed the shape features such as aspect ratio, elongatedness and perimeter to discriminate radish from weeds. In addition to roundness, seven invariant central moments (ICM) have also been included to identify corn and soybean from weed species (Woebbecke et al., 1995). However, shape features require the individual leaves to be isolated without overlap which is impossible in the sugarcane field scenario. Therefore shape features are not involved in the proposed feature set. Before 1998, low level texture features such as skewness, mean, variance (Franz et al., 1991) gray level co-occurrence matrix, angular second moment, inertia, entropy, local homogeneity are evaluated in soybean, maize and corn fields (Meyer et al., 1998). Later, Gabor wavelet texture feature occupies the feature set with tremendous improvement in weed/crop classification process (Tang et al., 1999).Texture features along with one of the modern classifiers such as Fuzzy Clustering, Bayesian Classifier, Support Vector Machine, and neuro-fuzzy classifiers (Tang et al., 2003; Cruz et al., 2013;Rainville et al., 2014; Zafar et al., 2015) have been employed in crop recognition systems.

III. BLOCK DIAGRAM: FEATURE VECTOR GENERATION AND CLASSIFICATION



3.1.Texture based weed detecting algorithm:

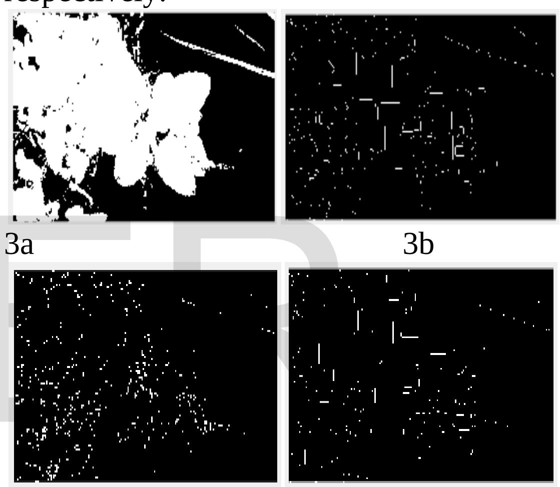
3.1.1. Greenness identification:

The first stage in a typical weed identification procedure is the segmentation of vegetation from the soil background. Several measures have been proposed for greenness identification (Romeo et al., 2013), but under poor environmental conditions most of them fail or do not work properly (Meyer and Neto, 2008). Colour based vegetation indices (R, G, B components) are frequently considered in this stage because of the fact that images of vegetation have a strong green component in comparison to background pixels. It is nearly impossible to achieve a 100% segmentation rate, especially without manual thresholding, due to uneven illumination and colour variation among different weed species or even among the same species at various growth stages and environmental conditions. Thus the objective of this step is to eliminate more than 99% of the soil and other residuals from the image and to retain the pixels of fresh vegetation in which the texture properties are not spoiled.

3.1.2. Morphological operations:

Morphological operations are performed to select the points at which the texture images are extracted. Guided texture extraction, computation of rotation invariant features, identification of optimal feature set and incorporation of application-specific real time classifier are the major contributions of this paper. Unlike the previous literatures, the centre point of texture images are determined by skeletonization of the binary image (3a) which is obtained in the greenness identification process. This step is based on the fact that morphologically distinguishable characteristics of the leaf (Bakker, 2012) are clearly revealed when the texture images are extracted from the centre part of the leaf. Skeletonization and branch points removal are the morphological operations used to guide the system in locating the points for texture extraction. Skeletonization is performed to determine the medial axis of the leaves in the cases where they are non- overlapped and to indicate the locus of centers of observed patterns in overlapping cases. The pixel-deletion based thinning methodology defined by Guo and Hall is applied in this step since it preserves the connectivity of the image pattern. Fig. 3a shows the binary image (3a) of a sugarcane crop. Fig. 3b displays the skeleton image obtained by applying parallel thinning with two sub-iteration algorithms (Guo and Hall,1989).The white pixels in the skeleton image provide the path to walkthrough in the texture extraction process. But this path is not deterministic as it possesses some branch points. Branch points are the pixels with more than two neighbours and it appears where the image components are connected. In some cases the misclassification in binary image also ends in false branch points. This misclassification is due to the non-green colour of the leaf edges, dust and other residues covering the leaf and scattering of light. In Fig. 3b, two false branch points and one real branch point appeared. Since the textures near the branch points (both real and false)
do not provide any useful information about the plant in the identification process and the presence of branch points create ambiguity while stepping through the white line in texture extraction procedure, they are removed from the skeleton. The branch points are thickened (5 pixel) before removing them in order to avoid the formation of noisy paths which are the side effects of false branch points. The thickened branch points are shown in Fig. 3c. The Fig. 3d presents the deterministic pathway which guides the texture pattern extraction process in fixing the midpoint of textures. It is obtained through the $\Delta = X.\Theta$

Where Δ, X and Θ skeleton image without branch points, skeleton image with branch points and image with only branch points respectively.



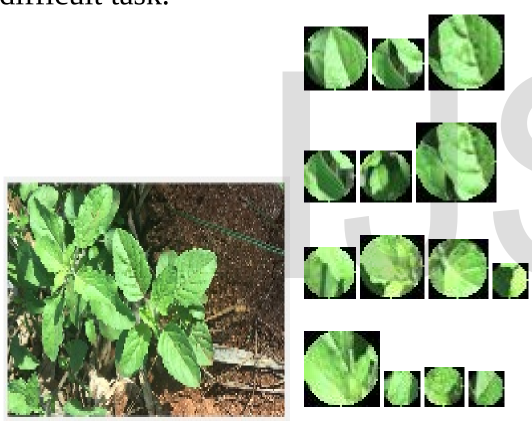
3a 3b 3c 3d

Fig.3 Results of Morphological operations

3.1.3. Leaf texture extraction:

The image obtained in the previous step (Δ) has isolated lines or curves. The end points of these curves are identified and solid circular masks of different scales (70 × 70to 32 × 32 in step -2) are spatially moved along the curves between the end points to obtain the texture pattern of optimal size. The size of the texture image corresponds to the width of vegetation at that point.

These texture images consist of either local leaf textures (midrib region) or texture patterns obtained from the overlapping leaves. The texture database of broad leaves mostly contain their local leaf textures in multiple scales. Contrarily, the texture database of narrow leaves mostly contain their global patterns. The green channel image was chosen for feature extraction since this channel had better gap between plants and soil than the other colour channels. This property of the green channel facilitates the extraction of more distinct texture features. Fig. 4a denotes the locations in which textures are extracted and Fig. 4b presents the crop texture database constructed from the green channel (gray scale) of the input image. Since this database was constructed by using mature (90 days crop) sugarcane leaves, most of the texture images are local leaf patterns and they contain a clear reference to the mid rib inside the image. Many weed species are common in Tamil Nadu farms. In that 2 weed species has been taken in this paper. Differentiating the grass and narrow leaved species from the crop is the most difficult task.



4(a) 4(b)

Fig.4Database of Crop

3.1.4. Computation of features:

Two types of features are computed and a deep study has been carried out to construct the optimal feature set for this application. The feature extraction methods analyzed in this study include: Gabor wavelet and the rotation-robust wavelet decomposition method. The overview of these texture extraction methods is given below.

3.1.5. Gabor wavelet:

In this research, the two dimensional(x and y) elementary Gabor wavelet function is used for weeds and crops feature extraction (Tang et al., 1999) and is defined as:

$$h(x,y)=\exp[x^{2j}x^2+y^2 2).\exp[j\pi x^j(x\cos\Theta+y\sin\Theta)]$$

Where $x=1/\sqrt{2}. j=0,1,2...\Theta\epsilon[0,2\pi]$ (1)

The Gabor wavelet function is a two–dimensional Gaussian envelop with standard deviation $\alpha^{=j}$ modulated by a sinusoid with frequency $\alpha j/2$ and orientation h. The different choices of frequency level j and orientation h are used to construct a set of filters. As the frequency of the sinusoid changes, the window size changes. This filter bank is composed of spatial domain filters that are generated from the elementary Gabor wavelet function. At each frequency level in the filter bank, there is a pair of filters that correspond to the real and imaginary parts of the complex sinusoid in the Gabor wavelet function. The filter output at each frequency level is computed as:

$$V[J]=\sqrt{xj^2+wj^2} \quad (2)$$

Where vj is the mean output of the real filter mask, and xj is the mean output of the imaginary filter mask, both at frequency level j, across multiple sample points. At every frequency level, the filter bank produces one texture feature. The filter bank is defined by the number and level of frequencies and the filter dimension or mask size. The filter orientation is fixed at 90º. Ten sample images containing two weed species and a crop are randomly selected for an experiment to select these filter bank parameters.

3.1.6. The Gray Level Co-occurrence:

The Gray Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features and it has been used for recognizing crop in the agricultural field (Wu and Wen, 2009). A number of texture features may be extracted from the GLCM. Nine prominent features namely, Maximum Probability, Energy, Entropy, Contrast, Cluster Shade, Cluster Prominence,

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Homogeneity, Inverse Difference Moment and Correlation are evaluated in this study.

3.1.7. Rotation-invariant wavelet features:

Rotation invariant feature vector generation for generalized textures has been discussed by many researchers in last decades. Among all these methods Hough transform based method greatly reduces the number of features and it also quickly identifies the image at various orientations. It is selected in order to neutralize the rotations in the image and various orientations of the patterns and textures.

IV.EXPERIMENTAL RESULTS

The classification processes are explained in this section. Results obtained using the Artificial neural network classifier is compared with the k-nearest neighbour classifier (k-NN) as k-NN has been used in the previous literatures for texture based classification**.**

4.1Probabilistic Neural Network

An artificial neural network (ANN) is an interconnected group of artificial neurons simulating the thinking process of human brain. One can consider an ANN as a "magical" black box trained to achieve expected intelligent process, against the input and output information stream. Thus, there is no need for a specified algorithm on how to identify different plants.PNN is derived from Radial Basis Function (RBF) Network which is an ANN using RBF. RBF is a bell shape function that scales the variable nonlinearly. PNN is adopted for it has many advantages (T. Master., 1993). Its training speed is many times faster than a any other network. PNN can approach a bayes optimal result under certain easily met conditions (D. F. Specht.,1990). Additionally, it is robust to noise examples. We choose it also for its simple structure and training manner. The most important advantage of PNN is that training is easy and instantaneous (D. F. Specht.,1990). Weights are not "trained" but assigned. Existing weights will never be alternated but only new vectors are inserted into weight matrices when training. So it can be used in real-time. Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast. The network classifies input vector into a specific class because that class has the maximum probability to be correct. In this paper, the PNN has three layers: the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.

V. CONCLUSION

Weeds are undesirable plants growing within a crop and they compete for resources such as nutrients, water and light. Without weed control, crop yields is highly affected asweeds can also cause problems such asharbouring pests and causing pathogen migration, interfering with harvest operations, and increasing costs of cleaning and drying the crop produce. As recent researches have established that weeds are distributed non-uniformly across the fields, weed control based on conventional practice of spread or lined applications of herbicide is therefore undesirable, in both economic and ecological conditions. In order to implement site-specific weed management, information on weed location is required. As manual surveying is a highly labour demanding job, automatic techniques using leaf-texture feature extraction and a new real time classification algorithm for identification of weeds have been proposed.

VI. REFERENCES

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