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Weed detecting robot in sugarcane fields using fuzzy real time classifier

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ABSTRACT

The objective of this research work is to propose a weed detecting robotic model for sugarcane fields that uses a fuzzy real time classifier on leaf textures. The differentiation between weed and crop and weed removal are the two challenging tasks for the farmers especially in the Indian sugarcane cultivation scenario. The automatic weed detection and removal becomes a vital task for improving the cost effectiveness and efficiency of the agricultural processes. The detection of weeds by the robotic model employs a Raspberry Pi based control system placed in a moving vehicle. An automated image classification system has been designed which extracts leaf textures and employs a fuzzy real-time classification technique. Morphological operators are applied to extract circular leaf patterns in different scales from the leaf images. An optimal set of features have been identified for the characterization of crops and weeds in sugarcane fields. A weed detecting robotic prototype is designed and developed using a Raspberry Pi micro controller and suitable input output subsystems such as cameras, small light sources and motors with power systems. The prototype's control incorporates the weed detection mechanism using a Raspbian operating system support and python programming. The designed robotic prototype correctly identifies the sugarcane crop among nine different weed species. The system detects weeds with 92.9% accuracy over a processing time of 0.02 s.

1. Introduction

Sugarcane is the second major cash crop in India (Murthy, 2010) besides cotton and it occupies about 3% of the total cropped area. Its share in value added agriculture is 6% and it contributes about 1.1% to the Indian GDP (Gross Domestic Product). The Indian production share alone amounts to more than 20% of the global share (Kshirsagar, 2008) and therefore it is an important source of income and employment for the Indian farming community. Sugarcane is considered as an energy crop, as it is used to produce, apart from sugar, other by-products such as renewable bio-electricity, bio-ethanol, bio-manure, alcohol, chemicals and fibre which improve ecological sustainability. More than five million farmers are either directly or indirectly involved in sugarcane cultivation in India (Solomon, 2014).

Sugarcane is a long duration crop which reaches its maturity in 11–12 months. Crop growth is very slow at the initial stage i.e. it takes 25–30 days to complete germination and another 90–95 days to complete tillering. Larger amount of nutrients and water is applied during the initial stages of growth as compared to the later stages. Sugarcane sets are planted continuously in rows with a spacing of 90 cm to 150 cm. The large amount of nutrients, moisture, solar radiation and wider spacing between crops also favor the growth of weeds in the sugarcane fields which prevent the crop from getting the nutrients.

Weed management is an essential practice in the sugarcane fields. Weeds compete with the crop for space, soil moisture, plant nutrients and solar radiation (Bakker, 2012). Especially in sugarcane fields, weeds reduce the germination and crop growth at the initial stage which in turn results in about 27% to 35% of yield loss. Hence, maintenance of the sugarcane field towards a weed-free condition becomes essential in the early growth phase (Rajenderkumar et al., 2014).

Weeds in these sugarcane fields are classified as grasses, sedges, broad leaved weeds and climbers wherein *Cynodon dactylon*, *Panicum* species, *Sorghum halopense*, *Chloris barbata*, *Dactyloctenium aegyptium* are family of grasses, *Cyperus iria* and *Cyperus rotundus* are family of sedges, Trianthema portulacastrum, Amaranthus viridis, *Portulaca oleraceae*, Commelina bengalensis, *Cleome viscosa* and *Chenapodium album* are broad leaved weeds and *Convolvulus arvensis*, *Ipomea sepiaria* and *Ipomea alba* are climbers (McMahon et al., 2000).

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Technological advances in computers and sensors have contributed to the use of automation in agriculture machinery, especially for weeding machines (Sujaritha et al., 2016). With automation, the weeding process is controlled electronically which reduces human intervention and optimizes the power provided by the machine.

There are several methods that can be used for weed control. Manual weed control is a method using bare hands or handheld tools to uproot weeds, while mechanical weed control involves the use of machines to perform weed control. Chemical weeding uses herbicides to control weeds, whereas biological weed control uses weed destroying organisms for weed control.

Modern agricultural practices introduce machine vision technologies in weeding. Machine vision is defined as the technique, method, or system of operating and controlling a process or mechanical device without human intervention. Machine vision technologies can be applied in two types of weed control methods: (i) Chemical weeding (ii) Mechanical weeding.

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 sugarcane is governed by the factors such as geographic location, planting date, weed species present and method of irrigation. Since sugarcane is a long-season crop, a broad spectrum of weed control is required. 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 sugarcane 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 will to a large degree determine the choice of herbicides in such combinations. Therefore, a mechanical weed control method which uses a rotavator blade and a robotic arm to uproot or remove the weeds from the field is used in the present system. This method increases tillering and sprouting, destroys insects (as they use the weeds as the initial breeding ground) and enhances aeration in the soil.

Machine vision (robotics) based mechanical weeding systems optimizes the power provided by the machine, and substitutes human input in a process with electronic hardware, sensors, actuators and software. 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. An automated machine acquires the knowledge(machine learning) to identify and differentiate the crop plants from weed plants, and subsequently, removes the weed plants with an appropriate uprooting device(Bakker, 2009).

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.

The above said methodologies have been employed in the commercial automated weed killing implements such as Photonic Detection Systems Pty Ltd (formerly Weed Control Australia), Weedseeker (formerly Patchen), and Rees Equipment. These commercial systems are used for broad leaved crops such as maize, corn and soybean where there is a stark difference in shape between the crops and weeds which is easily distinguishable. But the above systems might not be used for sugarcane, as the sugarcane crop bears a high level of similarity in shape and size with the weeds during the initial stages of growth.

Recently, the National Centre for Engineering in Agriculture (NCEA) has developed a weed spot sprayer which differentiates between Guinea Grass and sugar cane (Mccarthy et al., 2012). The structure detection algorithm that identifies the size, prominence, regularity and 'blobness' of the structure (developed by Frangi et al. (1998)) has been implemented in the above system. The values of the parameters have been empirically determined through iterative analysis on field images. This kind of empirical analysis might not fit all the environmental and soil conditions. Therefore, an algorithm which is suitable for Indian soil ecological conditions is necessary and it is to be verified pragmatically.

The weed detection system presented in this paper has four major steps. They are: (i) colour based greenness identification (ii) texture extraction (iii) feature vector generation and (iv) classification. The contribution of this paper lies in the texture extraction phase, where the morphological operations are used to extract the distinguishing characteristics between the weed and sugarcane leaves. The system also considers the surface texture of the leaf parts (venation) rather than the size and shape of the individual leaf and it is particularly robust due to its rotation invariance property. Also, the segmentation in agricultural field images is different from the segmentation in medical or any other scientific images because, in agricultural images, the part which is suitable for segmentation can be identified and that part alone can be used for classification. This reduces the computational load as not all the components of the image are segmented. Unlike past literatures, this flexibility in segmentation is utilized in the proposed system.

2. Materials and methods

The Architecture of this weeding system is given in Fig. 1. The three major components of the system include: (i) Image acquisition system, (ii) Processing system and (iii) Control system. These subsystems are explained in the following subsections.

2.1. Image acquisition system

In sugarcane fields, the sugarcane chip bud seedlings are planted in rows with inter-row distance of 150 cm and intra row distance of 60 cm. Two different cameras are employed for capturing inter - row and intra row images. An intex IT-105 web camera with 3264×2448 image capture resolution (Cam1) and a simple

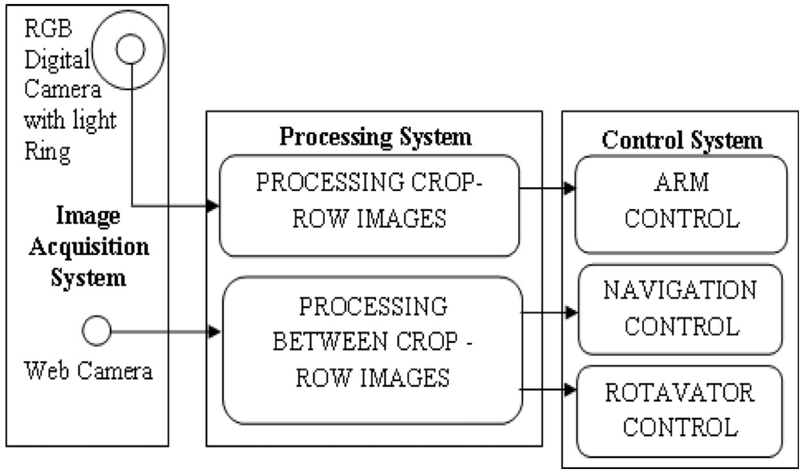


Fig. 1. Architecture of the weeding robotic model.

colour extraction algorithm are used in acquiring and processing inter-row images respectively, since it is assumed that all green leaved plants between crop-rows are weeds. The colour extraction process provides input to the microcontrollers that are responsible for the rotavator and wheel control.

The crop-row image acquisition is performed with a Raspberry pi native camera module (Cam2) which is capable of acquiring 2592 × 1944 px static images and also supports 1080p, 720p and 480p video with 30 to 60 fps (frames per second). This camera is supported in the latest version of Raspbian, Raspberry Pi's preferred operating system. A special light ring (Magideal Luxury Selfie Luminous LED Light Up Phone Ring) is fixed at the camera point to avoid the interference of shadows and other illumination related obstacles. Since the weeding process is performed at three stages in sugarcane fields, images are acquired in those stages for this work i.e. 15 days germinated shoot, one month maturity and three months crop. The present work mainly concentrates on processing intra-row images and classifying sugarcane crops with less than three months maturity and weeds in crop rows.

A solar energy based vehicle has been designed for image acquisition as shown in Fig. 2. The solar panel provides 20–40 V energy support for the functioning of this vehicle. Images are collected at various time intervals (morning, noon and evening) in a day. The database used for training the classification system consists of 300 images taken in outdoor environment under different lighting conditions. The experiments are conducted on the images of 10 different species (1 sugarcane + 9 weed species) and there are 30 images in each species.

Fig. 2. The weed detecting vehicle.

2.2. The processing system

It consists of two processes. The first process involves the application of colour extraction based algorithm on the images captured by web camera (Cam1) and the second process detects the weeds in crop row through extraction of texture features and application of Fuzzy Real Time Classification Algorithm (FRTCA) on Cam2 images. These processes are described as follows:

2.2.1. Colour based algorithm for robot navigation

Fig. 3 simulates the field environment and explains the colour based navigation process. The dominating colour is extracted at every moment during the navigation of the robot in the field by processing the Cam1 stream. The output of this process controls both the rotavator and the wheel movement. The colour powder sprayed at the end of the rows controls the robot navigation in the field. The green colour extracted from the weeds inside the field puts the rotavator down and spins it. The sand colour lifts the rotavator up and stops its spinning (Table 1).

Fig. 4 shows the hardware implementation of the colour extraction algorithm for navigating the robot in the field as well as controlling the rotavator. PIC 16F877A micro-controller and Raspberry Pi 2 (Model B+) are used in this phase. Raspbian Operating System is installed in Raspberry Pi controller and the python language is used for implementing the colour based algorithm.

2.2.2. Texture based weed detecting algorithm

The field images captured through Cam2 are processed in this phase. A real time supervised learning algorithm with a new internal texture extraction process using morphological operations has been presented in this subsection. Fig. 5 shows the block diagram of the feature vector generation method for our weed/crop classification system. It includes greenness identification, morphological operations, leaf texture extraction and feature extraction and selection.

2.2.2.1. 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). The light ring used in the present system

Fig. 3. Colour based navigation process.

Table 1
Colour based algorithm for wheel movement and rotavator actions.

Colour based algorithm for:	
Wheel movement	Rotavator actions

if blue
  Left turn
else if yellow
  Right turn
else
  Go straight
	if green
	  Down and spin
	else
	  Up and no spin

overcomes this problem by providing more or less uniform illumination on the field.

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 (even in the laboratory environment) 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 soil and other residuals from the image and to retain the pixels of fresh vegetation in which the texture properties are not spoiled.

A simple colour index which fully eliminates the blue channel is utilized in the present approach. This index is based on the fact that the pixel which appears green is the plant and the rest is background. A simple vegetative index indicated in Eq. (1) is used to binarize the colour field images for subsequent image processing and feature extraction procedures

$$Z(i,j) = \begin{cases} 1 & \text{if } G(i,j) - R(i,j) > t \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

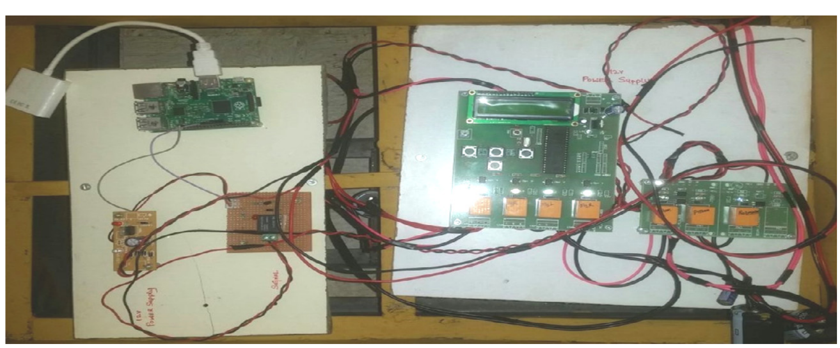


Fig. 4. The hardware implementation of colour based Algorithm.

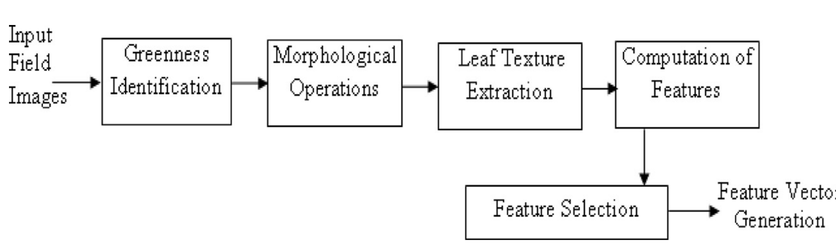


Fig. 5. Block diagram of the feature vector generation process.

(a) (b) (c)

Fig. 6. Results of greenness identification.

where G and R are Green and Red channels of the input colour image (I) respectively and Z is the binary image obtained though greenness identification process and 't' is the global threshold determined empirically which provides the correct segmentation rate of 98%.

Fig. 6a–c show the input colour image (I), the segmented image ($Z \cdot I$) and the output of the segmentation algorithm in which the pixels are distributed in the tri-dimensional RGB colour space (where red pixels belong to soil and residual class and blue pixels belong to vegetation class) respectively.

2.2.2.2. 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 (Z) 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. 7a shows the binary image (Z) of a sugarcane crop. Fig. 7b displays the skeleton image obtained by applying parallel thinning with two sub-iteration algorithms (Guo and Hall, 1989).

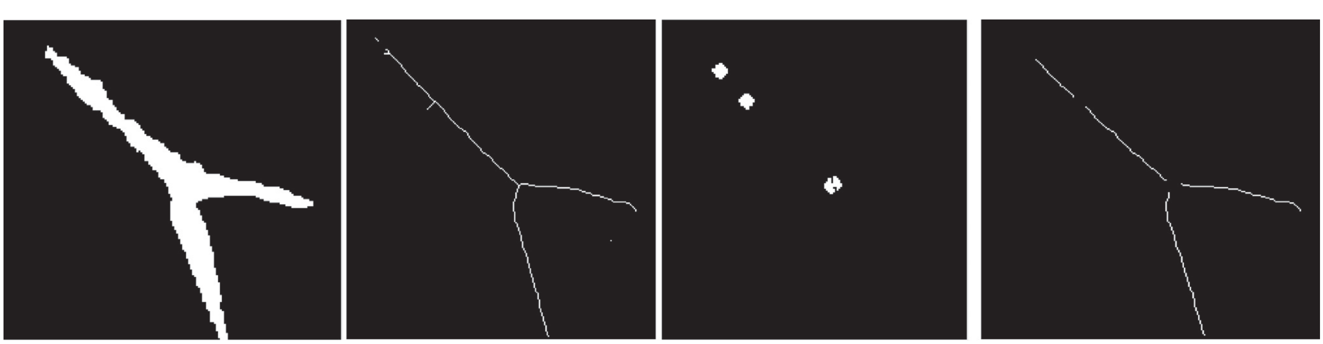
The white pixels in the skeleton image provide the path to walk through in the texture extraction process. But this path is not deterministic as it possesses some branch points. Branch points are the pixels with more than two neighbours and it appears where the image components are connected. In some 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. 7b, 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. 7c. The Fig. 7d presents the deterministic pathway which guides the texture pattern extraction process in fixing the midpoint of textures. It is obtained through the Eq. (2)

$$\Delta = X \cdot \Theta \quad (2)$$

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

2.2.2.3. 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 (71×71



(a) (Z) (b) X (c) Θ (d) (Δ)

Fig. 7. Results of morphological operations.

to 33×33 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. In order to make the features rotation invariant, circular area of the texture image is taken for feature value calculation. Initially the circular mask of size 71×71 is placed between the endpoints of a curve and it is verified as in Eq. (3).

$$\text{If } \mathrm{a} = \mathrm{b}, \quad \mathrm{k} \text{ is optimal (verified)} \tag{3}$$

$$\text{where} \quad a = \sum_{i=0}^{k-1}\sum_{j=0}^{k-1} z(i,j) \cdot m(i,j) \tag{4}$$

$$b = \sum_{i=0}^{k-1}\sum_{j=0}^{k-1} m(i,j) \tag{5}$$

$$m(i,j) = \begin{cases} 1 & \text{if } (i-r)^2 + (j-r)^2 \leqslant r^2 \\ 0 & \text{otherwise} \end{cases} \quad \mathrm{i,j} \cup 0 \ldots \mathrm{k}-1 \tag{6}$$

$$r = \left[\frac{k}{2}\right] \text{ and } z \subset Z \tag{7}$$

This verification process guarantees that the mask encloses only the vegetation, not the back ground. The mask size is reduced by 2 and the process is repeated till the optimal size is identified. Then the mask is moved to identify the next non-overlapping pattern. A complete walk is performed between each pair of endpoints and the leaf textures are extracted as in Eq. (8) by performing dot product between z, m and g where z is the binary image region at the location of mask, m is the circular mask selected at that region and g ($g \subset G$) is the green channel of the input image at that region.

$$T = z \cdot m \cdot g \tag{8}$$

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. 8a denotes the locations in which textures are extracted and 8b 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. Fig. 9 gives a picture of leaf-texture extraction in all the species that are taken for our experiment. Totally 9 weed species are common in Tamil Nadu sugarcane farms. Differentiating the grass and narrow leaved species from the sugarcane is the most difficult task.

2.2.2.4. Computation of features. Four 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: Normalized second-order gray level co-occurrence matrix, Laws' texture features, Gabor wavelet and the rotation-robust wavelet decomposition method. The overview of these texture extraction methods is given below.

2.2.2.4.1. Second order gray level matrix. 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, Homogeneity, Inverse Difference Moment and Correlation are evaluated in this study.

2.2.2.4.2. Laws' texture features. Laws developed a texture-energy approach that measures the amount of variation within a fixed-size window (Laws, 1980). A set of twenty 5×5 convolution masks is used to compute texture energy images (TE). The masks are computed from the following vectors: L5 (Level) = [1 4 6 4 1]; E5 (Edge) = [−1 −2 0 2 1]; S5 (Spot) = [−1 0 2 0 −1]; W5(Wave) = [−1 2 0 −2 1]; R5 (Ripple) = [1 −4 6 −4 1]. These TE images are normalized pixel-by-pixel with the L5L5T image (and then L5L5T is removed) and they are averaged corresponding to symmetrical kernels (such as R5L5 and L5R5). Taking into account that 20 out of 24 kernels (after removing L5L5) are symmetric to each other, 14 TR images are produced (R stands for 'Rotational invariance'). From each one of the 14 TR images, 5 first-order statistical measures (mean, standard deviation, range, skewness and kurtosis) are computed (i.e., 5 statistical features computed from 14 energy maps), giving a total of 70 texture features. But the mean statistical measure offers comparatively better classification accuracy than the other statistics.

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

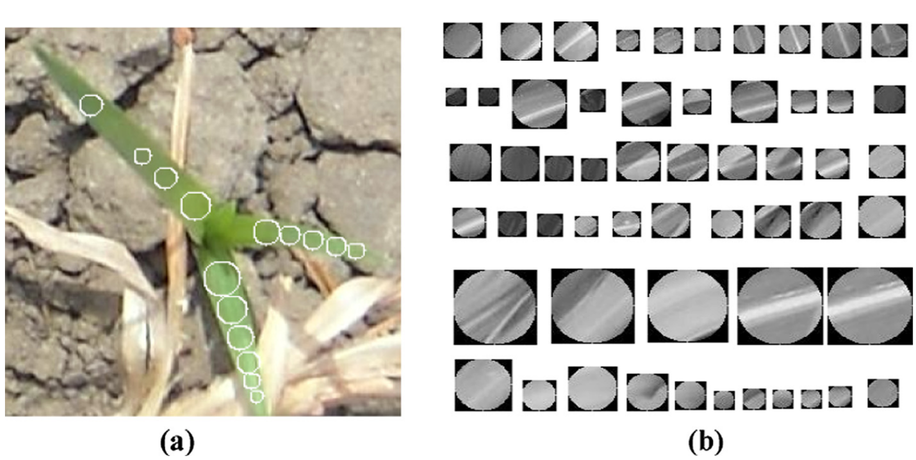


Fig. 8. Database of sugarcane leaf textures.

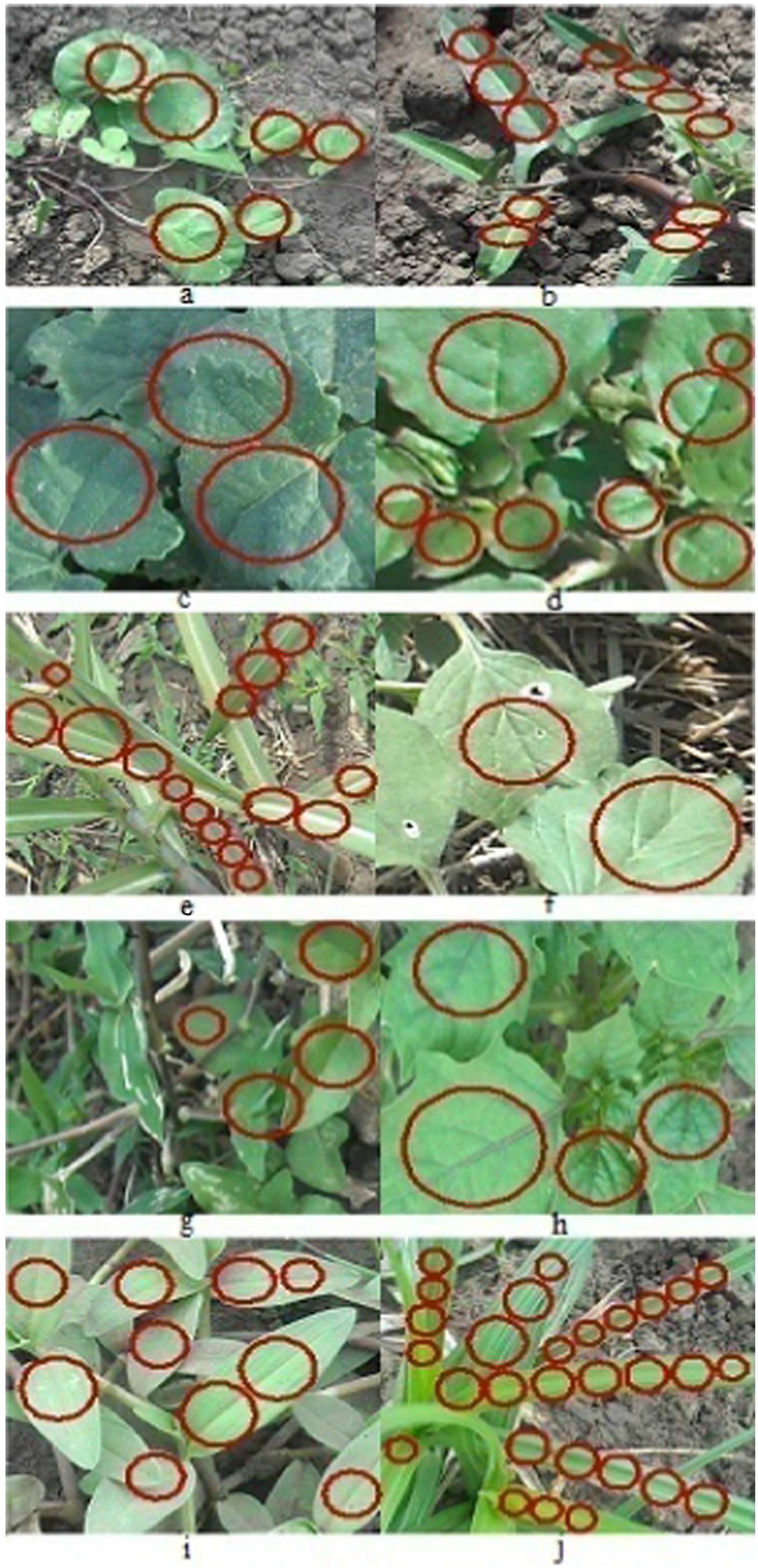


Fig. 9. Leaf-texture extraction from 10 species (1 crop + 9 weeds). a. Ipomea alba b. Convolvulus arvinse c.Cocciniagrandis d. Trianthemaportulacastrum e. Sugarcane f. Amaranthusviridis g. Cyanotisaxillaris h. Physalis minima i. Comalinabengalensis j. Cyperusrotundus.

$$h(x,y) = \exp\left[-\alpha^{2j}\frac{x^2+y^2}{2}\right].\exp[j\pi\alpha^j(x\cos\theta + y\sin\theta)]$$
$$\text{where } \alpha = \frac{1}{\sqrt{2}}, j = 0,1,2\ldots\theta \in [0,2\pi] \tag{9}$$

The Gabor wavelet function is a two–dimensional Gaussian envelope with standard deviation α^{-j} modulated by a sinusoid with frequency $\frac{\alpha^j}{2}$ and orientation θ. The different choices of frequency level j and orientation θ 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:

$$V[j] = \sqrt{\chi_j^2 + \omega_j^2} \tag{10}$$

where χ_j is the mean output of the real filter mask, and ω_j 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 90°. Forty sample images containing all nine weed species and sugarcane crop are randomly selected for an experiment to select these filter bank parameters. Four frequency levels from 4 to 7 and three mask sizes of 9 × 9 pixels, 13 × 13 pixels, and 17 × 17 pixels are investigated to measure the effect of frequency level and mask size on class separability.

2.2.2.4.4. 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 Kourosh and Hamid's radon transform based method greatly reduces the number of features and also quickly identifies the image at various orientations (Kourosh and Hamid, 2005). It is selected in order to neutralize the rotations in the image and the various orientations of the patterns and textures. Therefore, Kourosh and Hamid's feature extraction technique is utilized and redesigned due to the multi scale representation of the input leaf textures in this paper.

Fig. 10 shows the block diagram of feature vector generation scheme. The Radon transform is calculated for a circular area inside the texture image. To preserve the regularity of the radon transform for different orientations, a translation invariant wavelet transform is then employed to extract the frequency components and to calculate the features. The Radon transform of a grayscale (green channel) image (g(x,y)) is defined as:

$$R(r,\theta)[g(x,y)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x,y)\delta(r - x\cos\theta - y\sin\theta)dxdy \tag{11}$$

where r is the perpendicular distance of a line from the origin and θ is the angle formed by the distance vector. Since this transformation is invertible (Fourier slice theorem), the texture information is fully transferred to the next stage.

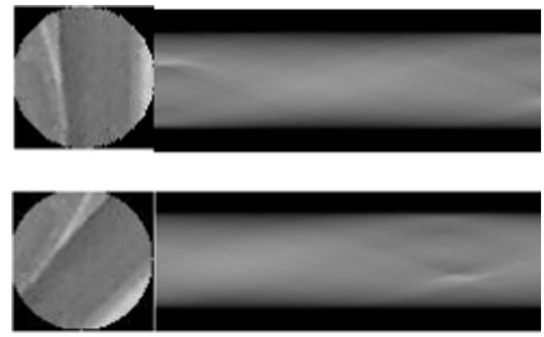


Fig. 11. Radon transform for original and rotated crop texture.

The important property of a radon transform is that the impact of rotation in the input is revealed as translation in the output along θ (which is demonstrated in Fig. 11). As shown, the rotation of input crop texture sample circularly shifts the transform output along horizontal axis and there is no change along vertical axis. Therefore, two different wavelet transforms are applied along each axis such as translation-invariant wavelet transform along θ and a regular wavelet transform along r in order to obtain undistorted features. This technique preserves the orthogonality of basis functions of the wavelet transform. This makes the extracted features uncorrelated and allows classification using less number of features. A family of wavelet functions and its associated scaling functions are used to decompose the radon output into different sub-bands. The energy and uniformity features are calculated for each sub-band (ζ) as follows:

$$Energy = \frac{1}{n_1 \times n_2}\sum_{x=1}^{n_1}\sum_{y=1}^{n_2}\sqrt{|\zeta(x,y)|} \tag{12a}$$

$$Uniformity = \frac{-1}{\log(n_1 \times n_2)}\sum_{x=1}^{n_1}\sum_{y=1}^{n_2}\frac{\sqrt{|\zeta(x,y)|}}{T_E}\log\left(\frac{\sqrt{|\zeta(x,y)|}}{T_E}\right)$$
$$\text{where } T_E = n_1 \times n_2 \times Energy \tag{12b}$$

where x,y are pixel values and n_1 and n_2 are the size of the image.

Five levels of wavelet decomposition with db2 wavelet basis is performed on the input texture images and their energy features are calculated. Three sub matrices corresponding to the highest resolution are removed and are not used for feature extraction. Because of real time data set, these sub matrices correspond to noise (like sand and thick edges) and are not suitable for classification. So, the features are calculated from 13 sub matrices.

2.2.2.5. Feature selection. Totally 48 features have been extracted from each texture image. But all these features may not have the same level of significance for classification. An optimal feature set that gives good classification percentage in less time is required

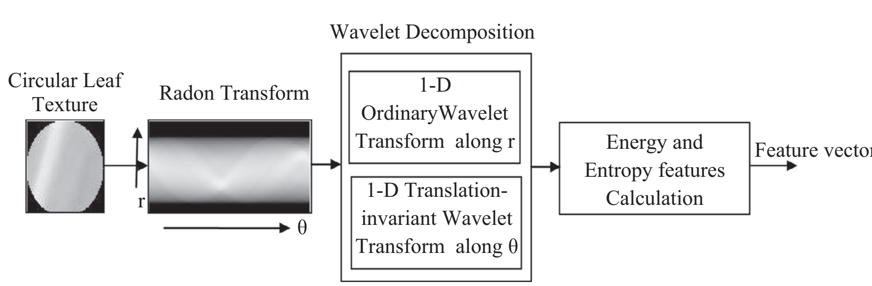


Fig. 10. Block diagram of Texture feature extraction.

by any real time system. Therefore, a feature selection technique that uses minimum Euclidean distance classifier is employed and finally 9 features are selected for the proposed weed identification system.

A systematic effort has been taken to analyze the performance of traditional and advanced features. The texture database with 980 images is used in this feature selection process. Among these textures, 600 (60 crop textures + 540 weed textures) images are taken as reference and 380 (38 crop textures + 342 weed textures) images are tested based on their feature values f_j^k and the correct classification percentage P_k for each feature k ([1,48]) is calculated using a simple Euclidean classifier as in Eq. (13).

$$P_k = \frac{1}{380}\sum_{j=1}^{380} C_j^k \times 100 \tag{13}$$

where

$$C_j^k = \begin{cases} 1 & class\left(\underset{i \in [1,600]}{\arg\min} \|f_j^k - f_i^k\|\right) = class(j) \\ 0 & otherwise \end{cases} \tag{14}$$

and class(x) gives the class of the texture image × (i.e. weed or crop) and 'i' is the train image index and 'j' is the test image index.

Table 2 shows the correct classification percentage $P_k$of the various texture features. Features with more than 65% of classification accuracy would be considered as good features. Since single feature is used for classification in this experiment, the classification performance would be less than 75%. But this experiment helps to find the good features from each texture extraction method for this weed/crop classification application. The features with correct classification percentage of more than 65% (G9, G10, G11, T6,

Table 2
Correct classification percentage obtained by different features that are extracted through different Texture Feature extraction methods.

Feature computation method	Specification			P_k
Gray level co occurrence matrix (GLCM)	Name	Features		
	M1	Maximum probability		60.1
	M2	Energy		62.4
	M3	Entropy		64.3
	M4	Contrast		64.1
	M5	Cluster shade		59.3
	M6	Cluster prominence		58.6
	M7	Homogeneity		62.3
	M8	Inverse difference moment		61.6
	M9	Correlation		62.4
Laws texture first order statistics: mean	Name	Energy map		
	T1	R5E5TR		64.6
	T2	R5S5TR		63.4
	T3	S5E5TR		62.3
	T4	S5S5TR		61.7
	T5	W5W5TR		60.7
	T6	E5E5TR		69.6
	T7	R5L5TR		54.2
	T8	E5L5TR		69.6
	T9	R5R5TR		54.3
	T10	W5E5TR		53.6
	T11	S5L5TR		56.5
	T12	R5W5TR		57.3
	T13	W5S5TR		52.4
	T14	W5L5TR		57.3
Gabor wavelet Orientation: 90°	Name	Frequency	Mask size	
	G1	4	9 × 9	59.3
	G2	5	9 × 9	59.7
	G3	6	9 × 9	59.4
	G4	7	9 × 9	58.2
	G5	4	13 × 13	63.9
	G6	5	13 × 13	62.3
	G7	6	13 × 13	63
	G8	7	13 × 13	64.1
	G9	4	17 × 17	68.9
	G10	5	17 × 17	69.6
	G11	6	17 × 17	69.5
	G12	7	17 × 17	64.7
Rotation –invariant wavelet features with DB2 and energy measure	Name	Level	Feature	
	W1	2	Horizontal detail	64.7
	W2	2	Vertical detail	63.9
	W3	2	Diagonal detail	64.3
	W4	3	Horizontal detail	63.3
	W5	3	Vertical detail	62.4
	W6	3	Diagonal detail	69.6
	W7	4	Horizontal detail	62.6
	W8	4	Vertical detail	61.4
	W9	4	Diagonal detail	74.9
	W10	5	Horizontal detail	63.4
	W11	5	Vertical detail	62.7
	W12	5	Diagonal detail	74.6
	W13	5	Approximation	75.3

Table 3
Cluster centers of crop and weed species.

	F1 (G9)	F2 (G10)	F3 (G11)	F4 (T6)	F5 (T8)	F6 (W6)	F7 (W9)	F8 (W12)	F9 (W13)
Sugarcane	0.53	0.34	0.71	0.66	0.51	0.37	0.62	0.33	0.19
Weed1	0.61	0.53	0.64	0.42	0.32	0.47	0.51	0.69	0.79
Weed2	0.41	0.19	0.79	0.69	0.91	0.29	0.12	0.93	0.24
Weed3	0.93	0.59	0.14	0.23	0.36	0.78	0.98	0.84	0.64
Weed4	0.85	0.72	0.24	0.13	0.16	0.43	0.59	0.79	0.82
Weed5	0.76	0.14	0.32	0.58	0.57	0.68	0.97	0.76	0.95
Weed6	0.31	0.33	0.75	0.64	0.97	0.98	0.12	0.78	0.73
Weed7	0.29	0.47	0.68	0.57	0.59	0.01	0.2	0.49	0.58
Weed8	0.89	0.76	0.45	0.31	0.05	0.19	0.01	0.73	0.43
Weed9	0.95	0.64	0.17	0.11	0.56	0.85	0.89	0.91	0.75

Table 4
Distance matrix between crop and weed.

	d_{i1} (G10)	d_{i2} (G11)	d_{i3} (G12)	d_{i4} (T6)	d_{i5} (T8)	d_{i6} (W6)	d_{i7} (W9)	d_{i8} (W12)	d_{i9} (W13)	$D = \sum_{j=1}^{9} d_{ij}$
Sugarcane	0	0	0	0	0	0	0	0	0	0
Weed1	0.0064	0.0361	0.0049	0.0576	0.0361	0.01	0.0121	0.1296	0.36	0.6528
Weed2	0.0144	0.0225	0.0064	0.0009	0.16	0.0064	0.25	0.36	0.0025	0.8231
Weed3	0.16	0.0625	0.3249	0.1849	0.0225	0.1681	0.1296	0.2601	0.2025	1.5151
Weed4	0.1024	0.1444	0.2209	0.2809	0.1225	0.0036	0.0009	0.2116	0.3969	1.4841
Weed5	0.0529	0.04	0.1521	0.0064	0.0036	0.0961	0.1225	0.1849	0.5776	1.2361
Weed6	0.0484	0.0001	0.0016	0.0004	0.2116	0.3721	0.25	0.2025	0.2916	1.3783
Weed7	0.0576	0.0169	0.0009	0.0081	0.0064	0.1296	0.1764	0.0256	0.1521	0.5736
Weed8	0.1296	0.1764	0.0676	0.1225	0.2116	0.0324	0.3721	0.16	0.0576	1.3298
Weed9	0.1764	0.09	0.2916	0.3025	0.0025	0.2304	0.0729	0.3364	0.3136	1.8163

T8, W6, W9, W12, and W13) are selected and given as input to the proposed Fuzzy Real Time Classifier (FRTC).

2.3. Control system

The control system receives the output from the previous classification stage in order to control the weed remover. The output of the texture based algorithm includes two classes of classification (weed and crop). If the output class is a weed, then the navigation stops and robot activates the arm. If the output class is a crop, then the weed remover does not stop. For the colour based algorithm, the outputs include green, yellow and blue. This facilitates the machine in removal of inter row weeds i.e. if the output is green then the rotavator blade is lowered and the weed is cut. If the output is yellow, the robot turns right by 90 degrees and if the output is blue, the robot turns left by 90 degrees. A total of seven DC motors are used in this system. A set of two motors with 20 W and 60 rpm rating is used for the rotavator, where one is used for up and down movement of the screw rod and the other is used for spinning the rotavator. Two motors with 30 W, 60 rpm are used for driving the robot. A PIC 16F877A microcontroller programmed with embedded C is used to control the four motors.

The other three motors with 20 W, 60 rpm rating are used for arm control at three points in order to simulate human hand movement. The second PIC 16F877A microcontroller programmed with embedded C is used to control these three motors. The power supply is provided by two means. A Rechargeable Battery with 12 V, 7 A capacity and a 20–40 W solar panel, which makes the robot environment friendly, are the sources of power.

3. Experimental results

The classification processes are explained in this section. Results obtained using the fuzzy real time 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 (Kourosh and Hamid, 2005).

3.1. Fuzzy Real Time Classifier (FRTC)

The fuzzy real time classification is designed to improve the classification performance in terms of accuracy and time through the incorporation of domain knowledge. Even though we have 10 species in the proposed application, only a two-class classifier is required for this purpose. The first class is sugarcane and the second class is weed. Therefore a simple classifier which discriminates the sugarcane from the weed is more than sufficient for this scenario. The proposed classification algorithm for real time classification is similar to a weighted Euclidean distance classifier. The weight assigned to each element of the distance vector is fuzzyfied based on its dissimilarity. Lesser the dissimilarity between the crop and the weed in terms of a particular feature value, more the weight is assigned to it. The weights are decimal values which lie in the interval [0, 1]. The weight assignment process is explained with a real-time dataset. Table 3 shows the normalized cluster centers of crop and weed species.

The distance matrix d_{ij} is calculated using Eq. (15):

$$d_{ij} = (C_{ij} - C_{sj})^2 \tag{15}$$

Where C_{sj} indicates cluster centre of jth feature of sugarcane crop, C_{ij} indicates cluster centre of jth feature of i, and 'i' is the class. Table 4 presents the distance matrix calculated for each class (sugarcane crop and weed species).

Then the weight matrix is calculated as follows:

$$W_{ij} = \frac{1 - d_{ij}}{D} \tag{16}$$

where

$$D = \sum_{j=1}^{9} d_{ij}. \tag{17}$$

Table 5 shows the weight matrix for each class. The classification process identifies the class of input leaf-texture by calculating weighted distance between feature vector of the samples and that

Table 5
Weight matrix.

	W_{i1} (G10)	W_{i2} (G11)	W_{i3} (G12)	W_{i4} (T6)	W_{i5} (T8)	W_{i6} (W6)	W_{i7} (W9)	W_{i8} (W12)	W_{i9} (W13)
Sugarcane	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
Weed1	0.1190	0.1155	0.1192	0.1129	0.1155	0.1186	0.1184	0.1043	0.0767
Weed2	0.1205	0.1195	0.1215	0.1222	0.1027	0.1215	0.0917	0.0783	0.1220
Weed3	0.1122	0.1253	0.0902	0.1089	0.1306	0.1111	0.1163	0.0989	0.1065
Weed4	0.1194	0.1138	0.1037	0.0957	0.1168	0.1326	0.1329	0.1049	0.0802
Weed5	0.1220	0.1236	0.1092	0.1280	0.1283	0.1164	0.1130	0.1050	0.0544
Weed6	0.1249	0.1312	0.1310	0.1312	0.1034	0.0824	0.0984	0.1046	0.0929
Weed7	0.1118	0.1167	0.1186	0.1177	0.1179	0.1033	0.0977	0.1156	0.1006
Weed8	0.1135	0.1074	0.1216	0.1144	0.1028	0.1262	0.0819	0.1095	0.1229
Weed9	0.1146	0.1267	0.0986	0.0971	0.1389	0.1071	0.1291	0.0924	0.0955

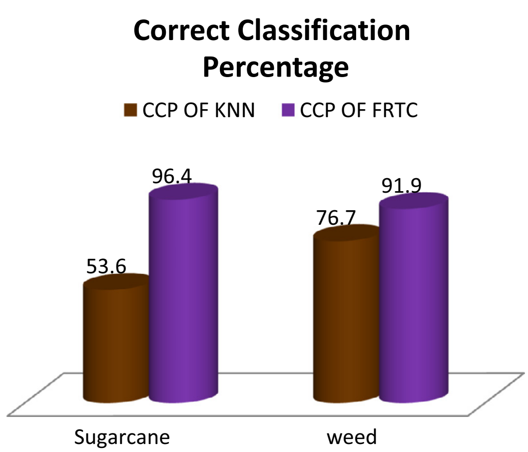


Fig. 12. Performance comparison between k-NN and FRTC.

of the query image. The class of the sample is assigned based on the minimum weighted distance between the query texture and the training samples. The textures that are classified as weeds are grouped into a single region and are marked for further processing.

3.2. Performance analysis

The proposed FRTC algorithm has been applied to 28 sugarcane crops and 99 (11 $\times$ 9 species) weeds in order to analyze the performance of the classifier. The correct classification percentage of the proposed FRTC is compared with a k- Nearest Neighbour Classifier (k-NN). The time taken for the classification of an image is 0.02 s. Fig. 12 depicts that the proposed algorithm outperforms in identifying both crop and weed. Even though the features of weed species such as Comalina bengalensis, Cyperus rotundus, and Convolvulus arvinse are very close to that of sugarcane crop, the proposed classifier improves the correct classification percentage of sugarcane from 53.6% to 96.4% and that of weed from 76.7% to 91.9%.

The performance of the weed detecting robotic model is analyzed by moving the vehicle in the sugarcane field and processing the images captured in Cam2. This experiment is carried out in three different stages of the sugarcane (30 days crop, 60 days crop and 90 days crop) and in three different lighting conditions (9 AM, 12 noon and 4 PM) during a sunny day. The growth stage, time of experiment, the number of crops and weeds analyzed, and the correct classification percentage of crop and weed are tabulated in table 6.

4. Conclusion

Weeds are undesirable plants growing with crops and they compete for resources such as nutrients, water and light. Without weed control, crop yield is highly affected as weeds can also cause problems such as harbouring pests and pathogens, 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 the 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 determination of weeds have been proposed. A new formulation for feature extraction, the rotation invariant and scale invariant texture analysis method and fuzzy real time classifier are the key ideas of the weed detecting system. A field robotic model in which the weed detection algorithm is implemented has been tested in different sugarcane fields and it gives an overall accuracy of 92.9% and processing time of 0.02 s.

4.1. Future extension

The design of the robotic arm is not described in this paper. The present research work will be extended to overcome the issues related to robotic arm movement and its synchronization with the rotavator, the vehicle movement and its path control. During

Table 6
Performance of the classifier under different growth stages and illumination conditions.

Growth stages	Time	Number of images used in the experiment	Correct classification percentage of crop (in %)	Correct classification percentage of weed
30 days	8 AM	40 crops + 60 weeds	92	90
	12 noon	40 crops + 60 weeds	90	92
	4 PM	40 crops + 60 weeds	90	89
60 days	8 AM	40 crops + 60 weeds	92	90
	12noon	40 crops + 60 weeds	92	92
	4 PM	40 crops + 60 weeds	95	90
90 days	8 AM	40 crops + 60 weeds	98	96
	12 noon	40 crops + 60 weeds	100	98
	4 PM	40 crops + 60 weeds	98	97

the course of the movement of the robot, it is possible that a deviation in the determined course might occur due to obstacles in the field. This can be rectified by mounting an accelerometer and gyroscope in order to track deviations and perform course correction actions. Alternatively, a drone can be used as a guidance system for the robot.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2017.01.008.

References

Bakker, T., 2009. An Autonomous Robot for Weed Control – Design, Navigation and Control PhD Thesis. Wageningen University. Department of Agricultural Engineering.

Bakker, H., 2012. Sugar Cane Cultivation and Management. Springer.

Cho, S.I., Lee, D.S., Jeong, J.Y., 2002. Weed-plant discrimination by machine vision and artificial neural network. Bio. Syst. Eng. 83 (3), 275–280.

Cruz, G., Jesús, M., Romeo, G., Pajares, G., Montalvo, M., Guerrero, J.M., Guijarro, M., 2013. A new expert system for greenness identification in agricultural images. Expert Syst. Appl. 40 (6), 2275–2286.

Frangi, A.F., Niessen, W.J., Vincken, K.L., Viergever, M.A., 1998. Multiscale vessel enhancement filtering. Lect. Notes Comput. Sci. 1496, 130–137.

Franz, E., Gebhardt, M.R., Unklesbay, K.B., 1991. Shape description of completely visible and partially occluded leaves for identifying plants in digital images. Trans. ASAE 34 (2), 673–681.

Guo, Z., Hall, R.W., 1989. Parallel thinning with two-subiteration algorithms. Comm. ACM 32 (3), 359–373.

Guijarro, M., Pajares, G., Riomoros, I., Herrera, P.J., Artizzu, X.P.B., Ribeiro, A., 2011. Automatic segmentation of relevant textures in agricultural images. Comput. Electr. Agri. 75, 75–83.

Kourosh, J.K., Hamid, S.Z., 2005. Rotation-Invariant Multiresolution texture analysis using radon and wavelet Transforms. IEEE Trans Image Proc. 14 (6), 783–795.

Kshirsagar, K.G., 2008. Impact of organic sugarcane farming on economics and water use efficiency in Maharashtra. In: International Water Management Institute Conference.

Lamm, R.D., Slaughter, D.C., Giles, D.K., 2002. Precision weed control system for cotton. Trans. ASAE 45 (1), 231–238.

Laws, K.I., 1990 Textured Image Segmentation, University of Southern California Report USCIPI 940 (Ph.D. Thesis).

McCarthy, C., Rees, S., Baillie, C., 2012. Preliminary evaluation of shape and colour image sensing for automated weed identification in sugarcane. Proc Aust. Soc. Sugar cane Technol 34.

McMahon, Gavin, Peter Lawrence, Tim O'Grady, 2000. Weed control in sugarcane, Manual of cane growing. Bureau of Sugar Experiment Stations, Indooroopilly. pp. 241–261.

Meyer, G.E., Hindman, T.W., Lakshmi, K., 1998. Machine Vision Detection Parameters for Plant Species Identification. SPIE, Bellingham, WA.

Meyer, G.E., Neto, J.C., 2008. Verification of colour vegetation indices for automated crop imaging applications. Comput. Electr. Agri. 63, 282–293.

Murthy, S.R.S., 2010. Economics of Sugarcane Production and Processing. Department of Economic Analysis and Research, National Bank for Agriculture and Rural Development. Mumbai. Occasional Paper- 54. pp. 1–200.

Perez, A.J., Lopez, F., Benlloch, J.V., Christensen, S., 2000. Colour and shape analysis techniques for weed detection in cereal fields. Comput. Electron. Agri. 25, 197–212.

Rainville, F.M., Durand, A., Fortin, F.A., Tanguy, K., Maldague, X., Panneton, B., Simard, M.J., 2014. Bayesian classification and unsupervised learning for isolating weeds in row crops. Pattern Anal. Appl. 17 (2), 401–414.

Rajenderkumar, Jayeshsingh, Uppal, S.K., 2014. Weed management in sugarcane ratoon crop. Indian journal of weed science 46 (4), 346–349.

Romeo, J., Pajares, G., Montalvo, M., Guerrero, J.M., Guijarro, M., 2013. A new expert system for greenness identification in agricultural images. Expert Syst. Appl. 40 (6), 2275–2286.

Solomon, S., 2014. Sugarcane agriculture and sugar industry in India: at a glance. Sugar Tech. 16 (2), 113–124.

Sujaritha, M., Lakshminarasimhan, Mahesh, Jude Fernandez, Colin, Chandran, Mahesh, 2016. Greenbot: a solar autonomous robot to uproot weeds in a grape field. Int. J. Comput. Sci. Eng. Commun. 4 (2), 1351–1358.

Tang, L., Tian, L.F., Steward, B.L., Reid, J.F., 1999. Texture-based Weed Classification using Gabor Wavelets and Neural Network for Real-time Selective Herbicide Applications. ASAE.

Tang, L., Tian, L., Steward, B.L., 2003. Classification of broadleaf and grass weeds using gabor wavelets and an artificial neural network. Trans. ASAE 46 (4), 1247–1254.

Weide, R.Y.V.D., Bleeker, P.O., Achten, V.T.J.M., Lotz, L.A.P., Fogelberg, F., Melander, B., 2008. Innovation in mechanical weed control in crop rows. Weed Res. 48 (3), 215–224.

Woebbecke, D.M., Meyer, G.E., Von Bargen, K., Mortensen, D.A., 1995. Shape features for identifying young weeds using image analysis. Trans. Am. Soc. Agric. Eng. 38 (1), 271–281.

Wu, L., Wen, Y., 2009. Weed/corn seedling recognition by support vector machine using texture features. Afr. J. Agric. Res. 4 (9), 840–846.

Zafar, N., Rehma, S.U., Gillani, S., Asghar, S., 2015. Segmentation of crops and weeds using supervised learning technique in improving knowledge discovery through the Integration of data mining techniques, IGI-Global. pp. 308–333.

Zhang, Y., Staab, E.S., Slaughter, D.C., Giles, D.K., Downey, D., 2012. Automated weed control in organic row crops using hyper spectral species identification and thermal micro-dosing. Crop Protection 41, 96–105.