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Abstract: Texture classification is a chic and trendy technology in image processing. Weed control is a major effect on agriculture. Large amount of herbicide has been used for controlling weeds. Certain areas in the agricultural field have more weeds. So, we require an automated visual system that can discriminate weeds from a given field image, which will reduce or even eliminate the amount of herbicide used. This would help farmers to use herbicides only in places where required. In this paper, Multiresolution Combined Statistical and Spatial Frequency (MRCSF) is used to discriminate the weeds from the crops and to classify them.

Keywords: texture; crop image; weed image; MRCSF; multiresolution combined statistical and spatial frequency; MRFM; Markov random field matrix; weed detection; SF; spatial frequency.

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1 Introduction

Texture (Haralick, 1979) can be defined as something that consists of mutually related elements. The major problem is that textures in the real world are often not uniform due to changes in orientation, scale or other visual appearance. In addition, the degree of computational complexity of many of the proposed texture measures is very high in texture classification. In Wang et al. (1998), the goal is to assign an unknown sample image to one of a set of known texture classes.

Weeds are "any plant growing in the wrong place at the wrong time and doing more harm than good" (Ahmad et al., 2007a). Weeds compete with the crop for water, light, nutrients and space, and therefore reduce crop yields and also affect the efficient use of machinery. A lot of methods are used for weed control. Among them, mechanical cultivation (Ahmad et al., 2006) is commonly practised in many vegetable crops to remove weeds, aerate soil and improve irrigation efficiency, but this technique cannot selectively remove weeds from the field. The most widely used method for weed control is to use agricultural chemicals. In fact, the success of agriculture is attributable to the effective use of chemicals. Agricultural production experienced a revolution in mechanisation over the past century. Identification of individual weeds in the field and locating their exact position is one of the most important tasks needed to further automate farming. Only with the technology to locate individual plants, can 'smart' field machinery be developed to automatically and precisely perform treatments. Herbicides are applied with a blanket treatment to whole field without regard to the spatial variability of the weeds in the field.

This practice results in some areas where no or few weeds exist receiving just as much chemicals as those areas with high densities of weeds. Obviously, if a more sophisticated chemical delivery system is developed, which apply chemicals where weeds exist and abstain where there are no weeds, chemical usage would be reduced and also more effectively placed. These practices would result in lower environmental loading and increased profitability in the agricultural production sector. Selectively spraying, spot spraying, or intermittent spraying are different names, which are attached to this herbicide application method. Thus, farmers need alternatives for weed control due to the desire to reduce chemical use and production costs as well as provide safety to underground water resources and the ecosystem. For some weed/crop situations (Graniatto et al., 2002), there are no selective herbicides. Since hand weeding is costly, an automated system could be feasible. A real-time weed control system can reduce or eliminate the need for chemicals between broad and narrow weeds. The purpose of this paper is to investigate a machine vision system to distinguish individual weeds into broad, narrow and little weeds.

2 Wavelet transform

A major advance in wavelet theory is the discovery of smooth mother wavelets whose set of discrete translations and dilations forms an orthonormal basis for $L^2(R)$ i.e., Wavelet Transform can be described in terms of its basis functions known as wavelets, where R is the real numbers and L^2 is the set of all functions that have bounded energy. The term basis function refers to a complete set of functions that can, when combined as a weighted sum, be used to construct a given signal. Application of the wavelet transform in practice is achieved using digital computers to transform sampled signals. For this reason, the Continuous Wavelet Transform (CWT) is replaced by the Discrete Wavelet Transform (DWT). Implementation of the DWT can be introduced by considering sub-band decomposition, the digital filter equivalent of the DWT. The sub-band components created by the filter bank structure or a true subsampled set of the CWT. Also, the wavelets used as the basis functions for this DWT form an orthonormal set. Representing the wavelet set as $k_{b,a}(t)$, orthonormality is defined by

$$\int k_{b,a}(t)\, k^*_{b,a}(t) \begin{cases} =1 & \text{if } b=b^* \text{ and } a=a^* \\ =0 & \text{for all other cases.} \end{cases} \tag{1}$$

Orthonormalities imply that no information redundancy is present. Orthonormalities also imply that any finite signal can be represented as a weighted sum of the basis functions and conversely that the signal can be perfectly reconstructed from a full set of weighted functions. The basic mathematical definition of a CWT is given by

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \psi^*((t-b)/a)\mathrm{d}t \tag{2}$$

where

'a' and 'b' are real.

*denotes complex conjugation.

$f(t)$ denotes the input 1D function.

'ψ' denotes the mother wavelet.

It is apparent that the transform is a function of two variables, 'a', which is called the scaling, or dilation variable, and 'b', which is called the time shift, or translation variable. This feature of translating and dilating a function results in orthogonal wavelet decomposition. CWT, a reformed definition for DWT, is given by

$$f(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l) 2^{-k/2} \psi(2^{-k}t - l) \tag{3}$$

where the dilation takes value of the form $a = 2^k$ and the translation at any dilation is given by $2^k . l$, where 'l' is again an integer. The values $d(k, l)$ are related to values of the wavelet transform.

$W(a, b) = W[f(t)]$ at $a = 2^k$ and $b = 2^k \cdot l$. This corresponds to sampling the coordinates (a, b) resulting in a process called dyadic sampling. The two-dimensional sequence $q(k, l)$ is commonly referred to as the DWT of $f(t)$.

3 Discrete Wavelet Transform

The DWT is sufficient for most practical applications and for the reconstruction of the signal. The DWT provides enough information, and offers a significant reduction in the computation time. The DWT can be defined as follows

$$F(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k,l) 2^{-k/2} \psi(2^{k}t - l) \tag{4}$$

where the dimensional sequence $d(k, l)$ is the DWT of $f(t)$. The DWT corresponding to a CWT function $W(a, b)$ can be obtained by sampling the coordinates (a, b). This process is called dyadic sampling because the consecutive values of discrete scales (Rao and Bopardikar, 2002) as well as the corresponding intervals differ by a factor of two. Then, the dilation takes the values of the form $a = k2$ and translation takes the values of the form $b = 2kl$ where k and l are integers. The value of $d(k, l)$ represents the discretised values of CWT W (a, b) at $a = 2kl$ and $b = 2kl$.

4 Multiresolution analysis

The Multiresolution formulation (Wang et al., 1998) is designed to represent signals where a signal event is decomposed into fine details, but it turns out to be valuable in the representation of signals, where a time-frequency (or) time scale description is desired even if no concept of resolution is needed.

The original image is applied through the low-pass decomposition filter (Sabeenian and Palanisamy, 2008) in row wise and decimate the two pass filtered image. The decimated image is applied to the same LPF column wise and gets decimated once again. The resulting image is the approximation of the original image. This is called the approximate coefficients.

The low-pass filtered and decimated image in row wise is again passed through the high-pass decomposition filter in column wise and the output of high-pass filtered image is again decimated. The resulting image (Wang and Liu, 1999) is the vertical detail coefficients of the original image.

Then, the original image is applied through the high-pass decomposition filter in row wise and the high-pass filtered image is decimated. The decimated image is applied through the same high-pass decomposition filter in column wise and again gets decimated. The resulting image is the diagonal detail coefficients of the original image.

The high-pass filtered and decimated image in row wise is again passed through the low-pass filtered in column wise and decimated again. The resulting image is the horizontal detail coefficient (Sabeenian and Palanisamy, 2008) of the original image.

5 MRCSF

Here, we introduced new method for texture image classification using MRCSF. MRCSF is a combination of first-order, second-order statistical properties along with Spatial Frequency (SF) of Multiresolution analysis.

The Pseudocode for MRCSF algorithm (Sabeenian and Palanisamy, 2009b)

- Obtain the original image.
- Apply DWT with ‘db4’ filter.
- Obtain MRF Parameter matrix for the wavelet-decomposed image samples. The way of determining Markov Random Field Matrix (MRFM) is given in detail in Section 5.1.
- Determine First-order statistical features like mean, variance, standard deviation, energy and the second-order statistical features like MRFM and Grey Level Co-occurrence matrix are extracted along with SF of the wavelet-decomposed samples. The way of determining SF is given in detail in Section 5.2.
- Combination of the above-mentioned features is called Multiresolution Combined Statistical and spatial Frequency (MRCSF) method (Sabeenian and Palanisamy, 2009b).
- MRCSF provides better classification rate when compared with remaining methods.

5.1 MRFM

Markov Random Field Matrix (MRFM) is constructed from the nine parameters ($\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4$ and ξ). MRF parameters (Sabeenian and Palanisamy, 2008) are extracted from 3×3 size image matrix as shown in Figure 1.

The procedure consists of the following steps:

1. Find the relationship between the centre pixel and its nearest neighbours of 3×3 matrix.
2. Obtain nine different MRF parameters from the eight neighbourhood system.
3. The parameter of β depends on two pixel relationship, γ depends on three pixel relationship and ξ depends on four pixel relationship.
4. MRF parameter matrix [M] output contains nine parameters so the size is 1×9 obtain transpose of M matrix [M^T] and multiply with M matrix. It provides 9×9 size MRF matrix (Sabeenian and Palanisamy, 2007).
5. Obtain MRF features from the MRF matrix.

Figure 1 Pixel i and its eight neighbours in the second-order neighbourhood system

i_1	i_2	i_3
i_8	I	i_4
i_7	i_6	i_5

5.2 Spatial Frequency calculation

Spatial Frequency (Sabeenian and Palanisamy, 2008) measures the overall information level or activity level in the regions of an image. The SF for an $M \times N$ block of an image is calculated as follows

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{5}$$

$$RF = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}[F(m,n)-F(m,n-1)]^2} \quad (6)$$

$$CF = \sqrt{\frac{1}{MN}\sum_{n=1}^{N}\sum_{m=2}^{M}[F(m,n)-F(m-1,n)]^2} \quad (7)$$

where RF and CF are the row and column frequency, respectively. When the images get more blurred, the spatial frequency also gets reduced accordingly. The higher the value of SF, the higher will be the contrast and quality of the image.

In each sub-band, individual pixels or group of pixels of the wavelet transform of the images are compared using SF that serves as a measure of activity at that particular scale and space. Other examples of such measures are absolute values of the pixel grey values, maximum absolute grey value of the group of pixels being compared and the variance.

A fused wavelet transform (Sabeenian and Palanisamy, 2009a) is then related by taking pixels from that wavelet transform that shows greater activity (information level) at the pixel location.

6 Texture classification using MRCSF

Initially, Image Training is done by 20 images from Brodatz album (Brodatz, 1968) having the size of 512×512 and 8 bit monochrome images like bark, bubbles, brick, grass, hole array, leather, pigskin, raffia, rough wall, sand, straw, water, weave, wood, wool (Arivazhagan and Ganesan, 2003), etc.

Image classification is done with 512×512, 256×256, 128×128, 64×64 size image regions. The features are extracted from the unknown input images and compared with features already stored in the library, by means of calculating distance vector given in equation

$$D(i) = \sum_{j=1}^{m} abs[f_j(x) - f_j(i)] \quad (8)$$

The classification ratio of texture images using various features is given in Table 1 (Sabeenian and Palanisamy, 2009b).

Table 1 Texture image classification ratio

S. No.	Texture images	Correct classification ratio (%) F1	F2	F3	F4
1	Bark	95	80	100	100
2	Bubbles	98	95	87.5	100
3	Brick	90	85	75	100
4	Calf Leather	95	87.5	100	95
5	Carpet	100	90	100	100
6	Grass	95	87.5	75	93
7	Hole Array	100	95	100	100
8	Metal Gate	100	80	100	100

Table 1 Texture image classification ratio (continued)

S. No.	Texture images	Correct classification ratio (%) F1	F2	F3	F4
9	Pigskin	90	85	100	100
10	Raffia	90	75	75	90
11	Rough Wall	95	88	100	100
12	Sand	90	90	87.5	93
13	Straw	85	95	50	93
14	Tile	90	98	87.5	93
15	Water	95	90	87.5	100
16	Weave	96	78	87.5	100
17	Wire Mesh	93	90	100	100
18	Wood	95	90	87.5	100
19	Wood Grain	98	90	100	100
20	Wool	80	85	100	100
	Over all correct classification rate	*93.6%*	*87.75%*	*90%*	*98%*

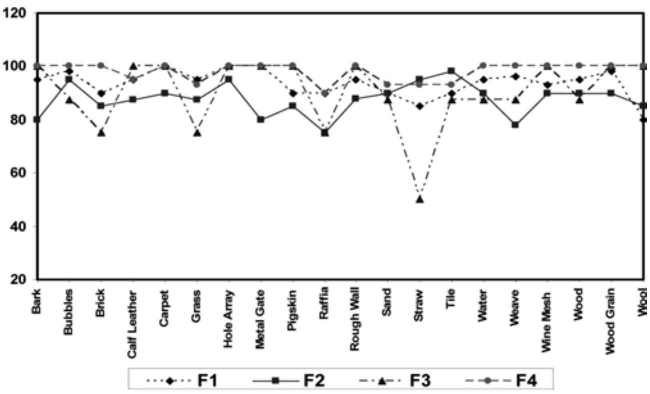
F1: Texture classification using wavelet statistical features

F2: Texture classification using second-order statistical features

F3: Texture Classification using SF

F4: Texture Classification using MRCSF.

Figure 2 Comparative analysis of texture image classification using MRCSF



7 Crop and weed discrimination

Weeds have a different colour pattern when compared with crop plant. Weeds can be easily discriminated from crops using their shape features. But since crop and weed occur in the same frame of the image, it is not possible to discriminate them using their shape. Hence, a better choice is to use the colour analysis as the basis to segment the weeds from the field image (Polder et al., 2007).

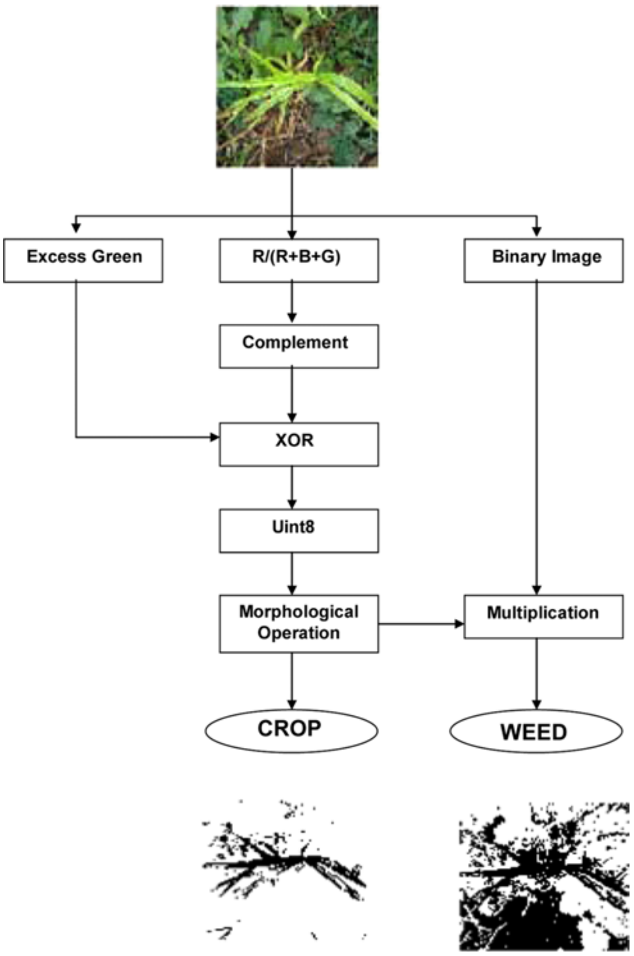
The image acquired is such that it captures both the crop and the weeds in the same frame. Weed segmentation requires two stages. First stage is separation of whole plants from the background. Second stage is separation of weeds from the main plant. Those pixels that are related to plants have greater green pixel value. The flow chart for weed discrimination is shown in Figure 3. Each block of the flow chart is explained in detail given here.

Excess Green Method is used to enhance the green pixel information so the remaining red and blue components are subtracted from the green pixel information. Offset Excess Green (OEG) value from the RGB image

$$OEG = 128 + (G - B) + (G - R). \tag{9}$$

As the light intensity changes, the three components red (R), green (G) and blue (B) change. In bright illumination, the soil has greater green component and plants in shade have lesser green component (Perez et al., 1997). This leads to misclassification. To reduce this illumination effect, calculate the ratio of *Red*/**(***Red* + *Blue* + *Green***)** for the input image, which defines the colour component ignoring the light intensity.

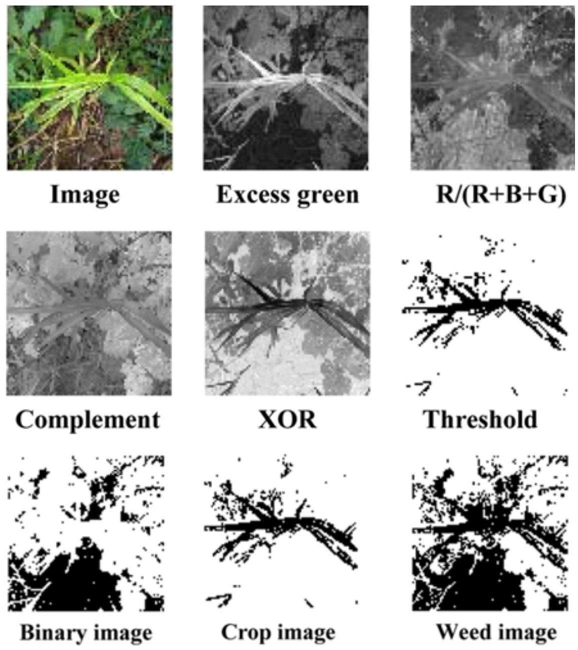
Figure 3 Weed discrimination using MRCSF (see online version for colours)



The complement of the resultant image is *X-OR* ed with the Excess Green image and the image matrix data is converted to unsigned 8 bit integer. *Morphological operation* 'skel' is performed to convert the resultant matrix to binary.

A logical operation is performed on the input image, such that if Green (G) > Red (R) and Green (G) > Blue (B), then '1' is set as pixel value, else '0' is set as pixel value, thus producing a *binary image*. This image is multiplied with the output of morphological operation to segment weeds from the image. Different stages output images are shown in Figure 4.

Figure 4 Crop and weed discrimination (see online version for colours)



8 Weed classification using MRCSF

Images are captured at a height of 2 feet from the field using digital camera with pixel rate of 7.4 Mega pixel of JPEG type and average size of 2048 × 1536. Pre-processing of field images prior to image classification and weed detection is essential. Pre-processing commonly comprises a series of sequential operations, which includes the adjustment, decorrelation, and Excess green, dwt2 approximation of the RGB field image. The flow chart for weed classification using MRCSF is shown in Figure 5.

Figure 6 shows the collection of different types of weeds from various agricultural fields like paddy field, sugarcane, sunflower, onion and tomato.

Image data acquired must be transformed from the acquired values to new values that are appropriate for colour reproduction or display. J = imadjust(I) maps the intensity values in greyscale image I to new values in J such that 1% of data is saturated at low and high intensities of I.

This increases the contrast of the output image J. It performs the adjustment on each image plane (red, green and blue) of the RGB image. Original Field image and its imadjust images are shown in Figures 7 and 8.

Figure 5 Flow chart for weed classification using MRCSF

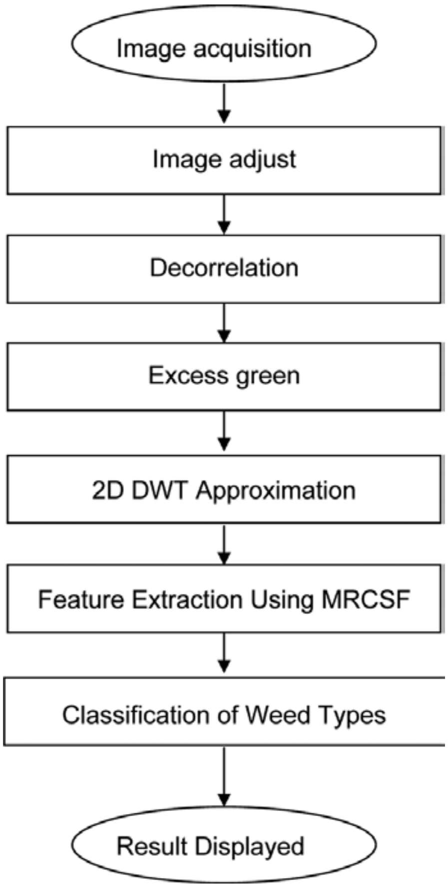


Figure 6 Different types of weeds in agricultural field (see online version for colours)

Figure 7 Original image (see online version for colours)

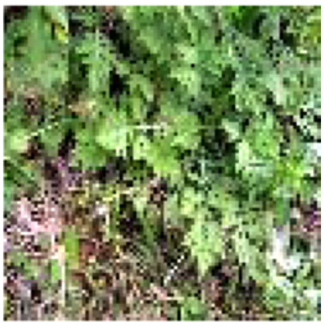


Figure 8 Imadjust image (see online version for colours)

Decorrelation techniques can be used to enhance, stretch colour differences found in each pixel of an image. The given field image is decorrelated, for better classification of weeds and the crops. The decorrelated image is shown in Figure 9.

Figure 9 Original and decorrelated image (see online version for colours)

Excess Green method involves in separating pixels into weed or background class is to calculate an OEG value from the RGB image. Each pixel in the RGB image is replaced with the following OEG value. Figure 10 indicates excess green output.

Figure 10 Excess green output

8.1 Feature extraction and classification

The first-order statistical features (Ahmad et al., 2007b) and second-order statistical features along with SF are extracted from the excess green information and stored in digital database.

The mean of the processed image of greyscale is calculated using equation

$$\mu = \frac{1}{MN} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} f(x_i, y_j) \tag{10}$$

where $f(x_i, y_i)$ is the intensity level of pixel (x_i, y_i) and M is the width of image and N is height of image. MN is total number of pixels in image.

The value of standard deviation, cluster shade and cluster prominence are calculated using the following equations

$$\sigma = \sqrt{\left[\frac{1}{76800}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(f(x_i, y_j) - \mu)^2\right]} \tag{11}$$

$$\text{Cluster shade} = \sum_i \sum_j ((i - \mu_i) + (j - \mu_j))^3 C(i, j) \tag{12}$$

$$\text{Cluster prominence} = \sum_i \sum_j ((i - \mu_i) + (j - \mu_j))^4 C(i, j). \tag{13}$$

$C(i, j)$: Grey level co-occurrence matrix

8.2 *Classification of weed images using MRCSF*

The types of weed images are classified using the following procedure.

1. First-order statistical features mean, standard deviation, second-order statistical features like MRFM, Cluster shade and Cluster prominence are calculated along with SF for multiresolution analysis.
2. The Feature values are less than threshold value (T_1) then the type of weed is classified as little weed.
3. If the featured value lies between T_1 and T_2, then the type of weed is classified as narrow weed.

   S = Multiresolution Combined Statistical and Spatial Frequency.

If S value is less than 145, the image is classified as little weed. Else if S value is between 145 and 170, classified the image as narrow weed. Else the image is classified as broad weed. 145 and 170 are threshold values.

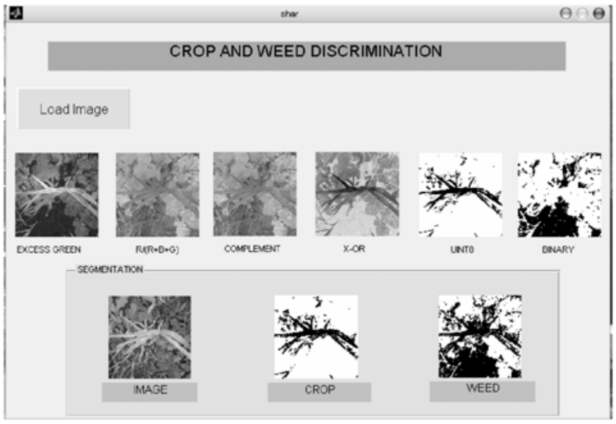
Cs = Cluster shade value. If Cs is less than –9e32, the image is classified as broad weed. Else if Cs value is between –9e32 and –2e32, classified the image as narrow weed. Else the image is classified as little weed.

Cp = Cluster prominence. If Cp is greater than 5e41, the image is classified as broad weed. Else if Cp value is between 1e41 and 5e41, classified the image as narrow weed. Else the image is classified as little weed.

9 Results and discussion

Crop Images are taken from the field using digital camera. It contains both crop and weed, so the weed portions are discriminated from the crop portion. Then, the type of the weeds is indicated whether the weed is narrow, little or broad. Figure 11 shows crop and weed discrimination using Excess green, $R/(R + B + G)$ ratio. After discriminating the weed from the crop, type of the weed is classified using MRCSF.

Figure 11 Crop and weed discrimination



The features are extracted from the narrow, broad and little weed then the classification done. Figure 12 shows the broad weed classification using MRCSF and Figure 13 indicates little weed detection using MRCSF.

Figure 12 Broad Weed classification using MRCSF

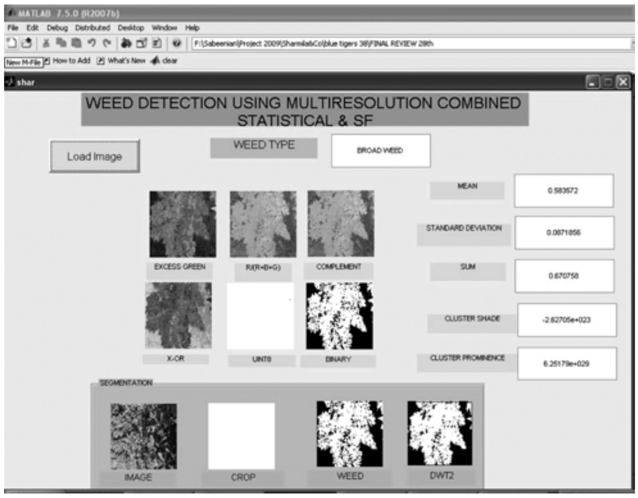
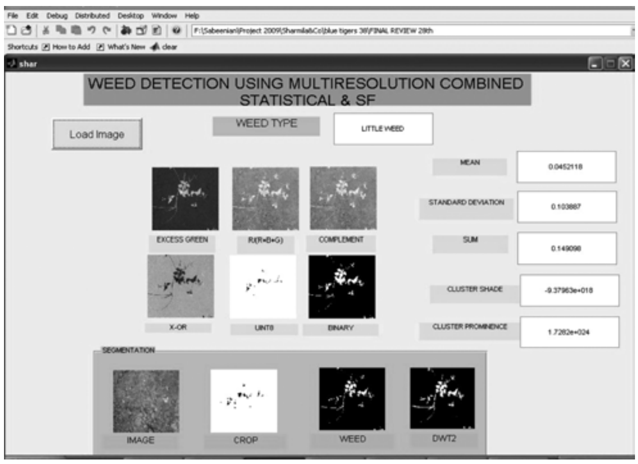


Figure 13 Little weed classification using MRCSF



Figures 14 and 15 indicate another sample of little and broad weed classification using MRCSF. Figure 16 indicates narrow weed classification using MRCSF.

Economic advantages

1 A big reduction of herbicide quantities (compared with the conventional uniform spray because weeds are patchy)

2 Elimination of manual labour, which is costlier and expensive

3 Safe food consumption

4 Protects grazing of poisonous weeds, e.g., Parthenium hysterophorus

5 Organic Cotton fields to prevent allergies

6 Inter-row weeding of food crops, e.g., Tomato, Tapioca, Lady's finger, etc.

7 Commercially in flower gardens, e.g., Rose, Jasmine, Blue Boar, etc.

8 *Export*: To reduce the percentage of weedicides in export products and prevent from ban.

Figure 14 Little weed classification using MRCSF Sample 2

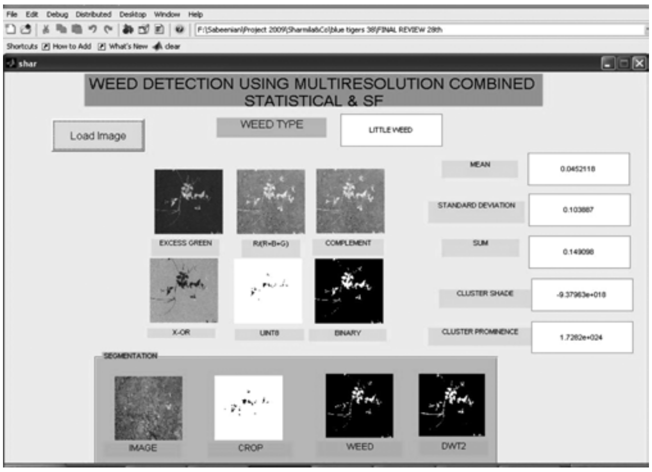


Figure 15 Broad weed classification using MRCSF Sample 2

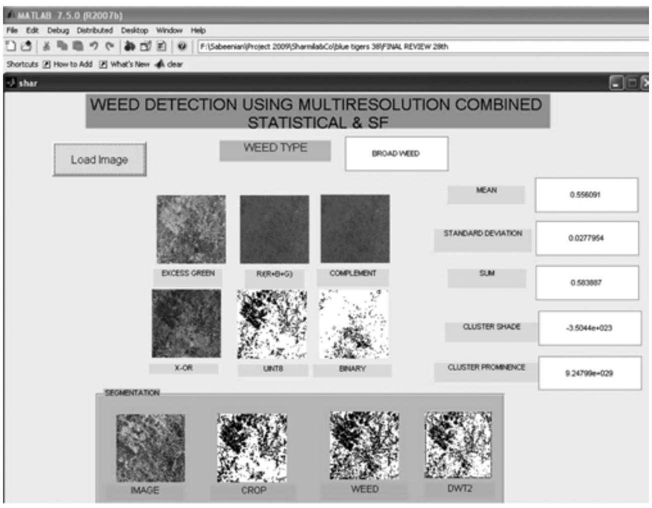
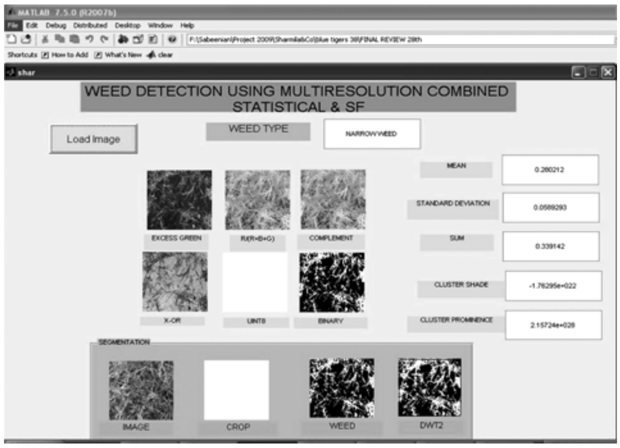


Figure 16 Narrow weed Classification using MRCSF



10 Conclusion

In Agricultural field, MRCSF identified the weeds from the crop field and also mentioned the type of the weed. It provides *99.3% classification rate for broad weed, 97.8% for narrow weed and 100% for little weed for 140 samples.*

In this paper, weed image, which has one dominant weed species, can be classified as broad, narrow or little. But, the case of more than one weed classes cannot be accurately classified. Further research is needed to classify mixed weeds. One way is to break the image into smaller region. With smaller region, there will be less possibility to find more than one weed classes in the same image. The visual system could be implemented on a robotic platform that would search out weeds and manually spray or simply cut the weeds.

References

Ahmad, I., Muhamin Naeem, A. and Islam, M. (2006) 'Real-time specific weed recognition system using histogram analysis', *Proceedings of World Academy of Science, Engineering and Technology*, Vol. 16, November, pp.145–148.

Ahmad, I., Muhamin Naeem, A., Islam, M. and Nawaz, S. (2007a) 'Weed classification using histogram maxima with threshold for selective herbicide', *Applications Proceedings of World Academy of Science, Engineering and Technology*, Vol. 21, January, pp.331–334.

Ahmad, I., Islam, M., Inayat Ali Shah, S. and Adnan, A. (2007b) 'Real-time specific weed recognition system using statistical methods', *Proceedings of World Academy of Science, Engineering and Technology*, Vol. 23, pp.478–482.

Arivazhagan, S. and Ganesan, L. (2003) 'Texture classification using wavelet transform', *Pattern Recognition Letters*, Vol. 24, pp.1513–1521.

Brodatz, P. (1968) *Texture A Photographic Album for Artists and Designers*, Rein Hold, New York.

Graniatto, P.M., Navone, H.D., Verdes, P.F. and Ceccatto, H. 'Weed seeds identification by machine vision', *Computers and Electronics in Agriculture*, Vol. 33, pp.91–103.

Haralick, R.M. (1979) 'Statistical and structural approaches to texture', *IEEE Proceedings*, Vol. 67, pp.786–804.

Perez, J., Lopez, F., Benlloch, J.V. and Christensen, S. (1997) 'Colour and shape analysis techniques for weed detection in cereal fields', *First European Conference for Information Technology in Agriculture*, Copenhagen, 15–18 June.

Polder, G., van Evert, F.K., Lamaker, A., de Jong, A., van der Heijden, G., Lotz, L.A.P., van der Zalm, T. and Kempenaar, C. (2007) *Weed Detection Using Textural Image Analysis*.

Rao, M. and Ajit Bopardikar, S. (2002) *Wavelet Transforms-Introduction to Theory and Applications*, Pearson Education Asia, Third Indian Reprint 2002.

Sabeenian, R.S. and Palanisamy, V. (2007) 'Comparison of MRF, wavelet and MRMRF features for classification of texture images', *Proceedings of the ICACC 2007 Organized by IEEE*, *IEEE SIPCICOM and ITFR held on February 2007*, pp.442–445.

Sabeenian, R.S. and Palanisamy, V. (2008) 'Comparison of efficiency for texture image classification using MRMRF & GLCM techniques', Published in the *International Journal of Computers Information Technology and Engineering (IJCITAE)*, Vol. 2, pp.87–93.

Sabeenian, R.S. and Palanisamy, V. (2009a) 'Texture based weed detection using multi resolution combined statistical and spatial frequency', *International Journal of World Academy of Science, Engineering and Technology, WASET*, (ISSN 2070-3740), Vol. 52, April, pp.549–553.

Sabeenian, R.S. and Palanisamy, V. (2009b) 'Texture based medical image classification of computed tomography images using MRCSF', Published in *International Journal of Medical Engineering and Informatics (IJMEI)*, Vol. 1, No. 4, pp.459–472, Published by Inderscience.

Wang, L. and Liu, J. (1999) 'Texture classification using multiresolution Markov random field model', *Pattern Recognition Letters*, Vol. 20, pp.171–182.

Wang, L., Liu, J. and Li, S.Z. (1998) 'Texture classification using wavelet decomposition with Markov random field models', *Proceedings of 14th International Conference on Pattern Recognition*, Vol. 2, pp.1613–1615.