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Texture Based Weed Detection Using Multi Resolution Combined Statistical & Spatial Frequency (MRCSF)

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***Abstract*—**Texture classification is a trendy and a catchy technology in the field of texture analysis. Textures, the repeated patterns, have different frequency components along different orientations. Our work is based on Texture Classification and its applications. It finds its applications in various fields like Medical Image Classification, Computer Vision, Remote Sensing, Agricultural Field, and Textile Industry. Weed control has a major effect on agriculture. A large amount of herbicide has been used for controlling weeds in agriculture fields, lawns, golf courses, sport fields, etc. Random spraying of herbicides does not meet the exact requirement of the field. Certain areas in field have more weed patches than estimated. So, we need a visual system that can discriminate weeds from the field image which will reduce or even eliminate the amount of herbicide used. This would allow farmers to not use any herbicides or only apply them where they are needed. A machine vision precision automated weed control system could reduce the usage of chemicals in crop fields. In this paper, an intelligent system for automatic weeding strategy Multi Resolution Combined Statistical & spatial Frequency is used to discriminate the weeds from the crops and to classify them as narrow, little and broad weeds.

***Keywords*—**crop weed discrimination, MRCSF, MRFM, Weed detection, Spatial Frequency.

I. INTRODUCTION

TEXTURE [5],[6] can be defined as something consisting 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 are very high in texture classification [6] 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” [1], [2]. 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 [1],[2] is commonly practiced in many vegetable crops to remove weeds, aerate soil, and improve irrigation efficiency, but this technique cannot selectively remove weeds from the field.

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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 mechanization over the past century. Identification of individual weeds in the field and location 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 exists and abstains where there are no weeds, chemical usage would be reduced and chemicals would be 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 under ground water resources and the ecosystem. For some weed/crop situations [3] 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 in to broad, narrow and little weeds.

II. RELATED WORKS

For automatic weed monitoring in cultivated a crops, two general approaches have typically been used [1],[2].The first is to detect certain geometric differences between the crop and weeds, such as leaf shape or plant structure. The second general approach is based on differences in spectral reflectance. There may also be a difference in location of the crop compared with the weed. The feasibility of using leaf shape [2] for plant identification: The initial investigation was limited to individual plants (three crop and five weed species) viewed against a soil background, in laboratory conditions.

The differences between vegetation and soil reflectance in the near-infrared region, proved successful for segmenting plants from a soil background.

The potential of remote sensing techniques[2],[3] for crop protection in the field, and suggested that one way to distinguish between weeds and crops was by examining the temporal patterns of vegetation indices throughout the growing season. The potential for distinguishing weeds from agricultural crops [4] based on their relative spectral reflectance characteristics. However, they added that it might be necessary to look at identifying groups of weeds rather than individual species, in real agricultural environments.

The shape feature [9] analysis for discriminating between monocots and dicots: The plants used in that experiment were grown individually in pots and colour information was used to separate target plants from the soil and residue background. Three different approaches [4],[9] to identify weeds in wheat fields using machine vision: colour analysis, shape analysis and texture analysis. They used black-white digital images with various colour filters, under laboratory conditions. The red and green filters were effective in detecting reddish stems of some weed species. Shape parameters were effective in distinguishing single leaves of broadleaf weeds from wheat leaves.

Since in practice there are only two types of herbicides used for broad weed , narrow weed .The objective of our work is to develop an algorithm that can identify the presence of weeds from the crop field and classify the type of the weed as broad, narrow and little.

III. WAVELET TRANSFORM

The Multi resolution formulation [11] 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 [5] 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 as the approximate coefficients.

The low pass filtered and decimated image in row wise in 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 [11],[12] 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 [12] 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 [12] of the original image.

IV. MRCSF

Here we introduced new method for texture image classification using Multi Resolution Combined Statistical and spatial Frequency (MRCSF). MRCSF is a combination of first order, second order statistical properties along with spatial frequency of Multi resolution analysis.

A. MRFM

Markov Random Field Matrix constructed from the 9 parameters ($\beta_1, \beta_2, \beta_3, \beta_4, \gamma_1, \gamma_2, \gamma_3, \gamma_{4,} and \xi$). We used 3x3 size matrix of image gray levels and extracted MRF parameters [5], [7] from that matrix.

The procedure consists of the following steps:

1. Find the relationship between the center pixel and its nearest neighbors of 3x3 matrix.
2. Obtain 9 different MRF parameters from the 8 neighborhood 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 9 parameters so the size is 1x9.obtain transpose of M matrix [M^T] and multiply with M matrix .It provides 9x9 size MRF matrix.
5. Obtain MRF features from the MRF matrix.

i_1	i_2	i_3
i_8	I	i_4
i_7	i_6	i_5

Fig. 1 Pixel i and its eight neighbors in the second order neighborhood system.

B. Spatial Frequency Calculation

Spatial Frequency [8],[9] measures the overall information level or activity level in the regions of an image. The spatial frequency for an MxN block of an image is calculated as follows

$$SF = \sqrt{(RF)^2 + (CF)^2} \tag{1}$$

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

$$CF = \sqrt{\frac{1}{MN}\sum_{n=1}^{N}\sum_{m=2}^{M}[F(m,n) - F(m-1,n)]^2} \tag{3}$$

Where RF and CF are the row frequency and column frequency respectively. When the images get more blurred, the spatial frequency also gets reduced accordingly. Higher the value of spatial frequency, 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 spatial frequency (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 gray values, maximum absolute gray value of the group of pixels being compared, and the variance.

A fused wavelet transform [3],[7] is then related by taking pixels from that wavelet transform that shows greater activity (information level) at the pixel location.

V. TEXTURE CLASSIFICATION USING MRCSF

Initially Image Training is done by 20 images from brodatz album[8],[10] having the size of 512 x 512 and 8 bit monochrome images like bark, bubbles, brick, grass, hole array, leather, pigskin, raffia, rough wall, sand, straw, water, weave, wood, wool[8],[10] etc.

Image Classification is done with 512x512, 256x256, 128x128, 64x64 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

$$D(i) = \sum_{j=1}^{m} abs[f_j(x) - f_j(i)] \tag{4}$$

The Classification ratio of texture images using various features are given below in Table 1.

TABLE I
TEXTURE IMAGE CLASSIFICATION RATIO

S.No	Texture Images	F1 (%)	F2 (%)	F3 (%)	F4 (%)
1	Bark	96	80	100	100
2	Bubbles	98	95	87.5	100
3	Brick	90	85	75	100
4	Calf Leather	95	87	100	95
5	Carpet	100	90	100	100
6	Grass	96	87	85	98
7	Hole Array	100	96	100	100
8	Metal Gate	100	80	100	100
9	Pigskin	90	85	100	100
10	Raffia	90	75	75	90
11	Rough Wall	96	88	100	100
12	Sand	90	90	87.5	95
13	Straw	85	94	90	95
14	Tile	90	97	87.5	100
15	Water	95	90	87.5	100
16	Weave	96	78	87.5	100
17	Wire Mesh	93	90	100	100
18	Wood	95	89	87.5	100
19	Wood Grain	97	92	100	100
20	Wool	80	87	90	90
Over All Correct Classification Rate (%)		**93.6**	**87.75**	**88.12**	**98.1**

F1: Texture Classification using Wavelet Statistical Features
F2: Texture Classification using second order Statistical Features
F3: Texture Classification using Spatial Frequency
F4: Texture Classification using MRCSF.

MRCSF can be applied to all the 112 images from brodatz album and the classification rate increased 92.2%.out of 2352 samples 2170 samples are correctly classified.

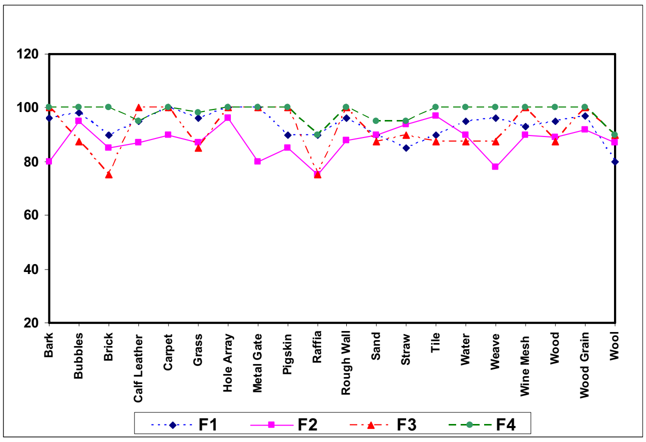

Fig. 2. Comparative Analysis of Texture Image Classification using MRCSF

It is observed that from the table1 and the Fig 2 MRCSF provides 98% correct classification rate than compare to other three features. The same algorithm is used to discriminate the weed portion from the crop and also classify the type of the weed

VI. CROP AND WEED DISCRIMINATION

Weeds have a different color pattern when compared to 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 color analysis as the basis to segment the weeds from the field image.

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 Fig 7.

The "EXCESS GREEN" method is used to enhance the green components of the image. In that excess green [1] method green values are multiplied with two times and the red, blue components are subtracted from the threshold value. 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. This leads to misclassification. To reduce this illumination effect, we calculate the ratio of Red / (Red+Blue+Green) for the input image, which defines the color component ignoring the light intensity. 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) && 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.

VII. 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 X 1536.Preprocessing of field images prior to image classification and weed detection is essential. Preprocessing commonly comprises a series of sequential operations, 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 Fig 8.

Image data acquired must be transformed from the acquired values to new values that are appropriate for color reproduction or display. J = imadjust(I) maps the intensity values in grayscale 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.

Fig. 3.Original image

Fig. 4. Imadjust image

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

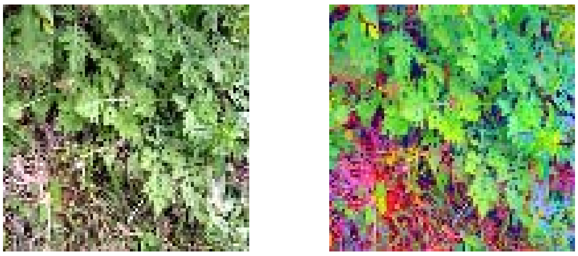

Fig. 5. Original & Decorrelated Image

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

$$OEG = 128 + 2G - B - R \qquad (5)$$

Fig. 6. Excess Green output

A. Mean and Standard Calculation

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

$$\mu = \frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1} f(x_i, y_j) \qquad (6)$$

The standard deviation of the processed image of grayscale is calculated using equation

$$\sigma = \sqrt{\frac{1}{76800}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(f(x_i, y_j) - \mu)^2} \qquad (7)$$

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

B. Classification of weed Images using MRCSF

The type of weed images are classified using the following procedure:

1. First order statistical features Mean, Standard deviation,
2. Second order statistical features like MRFM, Cluster shade and Cluster prominence are calculated along with spatial frequency for multi resolution analysis.
3. The Feature values are less than threshold value (T_1) then the type of weed is classified as Little Weed.
4. If the featured value lies between T_1 and T_2 then the type of weed is classified as Narrow weed.
5. The featured values are greater than the threshold value (T_2) then it is classified as Broad weed.

VIII. RESULTS & 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 are indicated whether the weed is narrow, little or broad. Fig 9 shows crop and weed discrimination using Excess green, R/(R+B+G) ratio. After discriminated the weed from the crop then type of the weed classified using MRCSF. The features are extracted from the narrow, broad and little weed then the classification done based on threshold value with respect to features.

Advantages:
1. A big reduction of herbicide quantities (compared with the conventional uniform spray because, weeds are patchy.)
2. Manual labor is costly and expensive.
3. Safe food consumption.
4. Protects Grazing of poisonous weeds. Ex: Parthenium hysterophorus
5. Organic Cotton fields to prevent allergies.
6. Inter-row weeding of food crops. Ex: Tomato, Tapioca, Lady's finger etc.
7. Commercially in flower gardens. Ex: Rose , Jasmine Blue Boar etc

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

IX.CONCLUSION

In Agricultural field MRCSF identified the weeds from the crop field and also mention the type of the weed. It provides 99.3% for broad weed 98.8% narrow weed and 100% for little weed for 200 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.

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