Image Processing Methods for Identifying Species of Plants

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Abstract: **More selective methods for applying agricultural herbicides on fields can result in substantial cost savings. Three image processing methods were tested for their ability to identify four different images of plant species. First two images were different and the other two were similar. The images are preprocessed by segmentation and spatial filtering using the Color Chromaticity Chart. The test results provide evidence that texture based methods can provide a useful metric for distinguishing between some species of plants.**

I. INTRODUCTION

Agricultural practices that uniformly treat large field areas are changing. There is a great deal of interest in technologies and practices that customize the application of seed, fertilizer, herbicides and other substances on a much smaller scale, even down to the individual plant. Researchers in Australia have developed a sprayer control system that activates individual nozzles based on the presence of plants and thereby dramatically reduces the cost of weed control in chemical fallow operations. The system is based on the spectral reflectance properties of the vegetation.

The application of targeted spraying systems in-crop requires the development of real-time methods for distinguishing between weeds and crop and between different weed species. Some research into electronic plant recognition has been reported using geometrical properties such as leaf elongation and moments of inertia [9]. These methods require the image segmentation of individual plants which is difficult in a field setting. Other methods with promise involve color spectral signatures. Texture based methods do not need individual plants to be isolated and can be routinely applied to the full image. They can be relatively insensitive to the orientation and scale of plant images. The ability to locate and identify plant species leads to many applications of useful control system [7].

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If a plant or row of plants can be located in a field using vision then it is possible for a tractor or other vehicle to automatically steer itself along the row and free the driver to do other tasks. The ability to detect weeds from within crops could lead to the possibility of localized spraying of herbicides thus reducing chemical waste, crop damage and environmental pollution.

The general objective of this research is to investigate the potential of using image processing techniques on plants spatial characteristics as an alternative or supplemental plant identification method. It also evaluates several texture based methods. The plants were photographed at a height of 1m. These photographs were scanned and converted from TIFF image format to binary RGB 256 x 256 x 8 bits. A black and white image was generated from RGB format image file. Both color and black and white images were used in different image processing techniques. Pre-processing was performed to convert these files into segmented, filtered, black/white and textured image files. using a Color Chromaticity Chart. A spatial mask filter was used to remove the effect of soil and stones. Additional filtering was required for noise reduction.

II. PREPROCESSING

For image analysis the first step is to segment the image. Segmentation subdivides an image into its constituent parts. It partitions the image space into meaningful regions such as the plant canopy portion excluding ground, and stones [8]. Segmentation for a monochrome image is based on discontinuity and similarity. Discontinuity partitions the image based on abrupt changes. It is used for detecting isolated points, lines, edges in an image. Similarity is based on thresholding and region growing. This thresholding is applied for the static plant images. Two segmented images were produced using these methods: one binary and the other retaining several gray levels to obtain more texture. The initial segmentation was based on the color cromaticity chart. The plant color is assumed green. The equation for separating the green color information from the image was developed as follows.

Threshold limit = 0.83R + Intercept (1)

The characteristics to differentiate one color from another are brightness, saturation, hue. Hue and saturation together are called chromaticity. The color chromaticity diagram shows color composition as a function of R, G and B plane [3]. As green color is predominant in the upper part of the chromaticity chart the equation of the line will separate green plant from the rest of the image by varying Y intercept. The original images are as shown in Fig. 4, Fig. 5, and Fig. 6. The segmented image is shown in Fig. 7.

The use of spatial masks for image processing usually is called spatial filtering and the masks themselves are called spatial filters. Smoothing filters are used for blurring and for noise reduction. Blurring is used for removal of small details from an image prior to object extraction. The extra information present in the image like ground, stones has to be removed as it may lead us to wrong results fig. 8. One of the principal difficulties of the smoothening method discussed is that it blurs edges and other sharp details. The method used is particularly effective when the noise pattern is due to small pebbles, soil patches with similar color with plant that consists of strong spike like component. The characteristics to be preserved is texture. The window size and threshold level is selected by the user. If more information in terms of gray levels is present in the window then the window is replaced by the texture information from the black and white input image. This method filters noise or scattered patches created due to stones on the ground. Software for segmentation, spatial filter, and thresholding was developed using C language.

III. Frequency Domain Method

The fourier transform is a single-band processes. The 3-band color images needed to be adapted by either selecting only one of the original red, green or blue (R, G, or B) bands, or generating a forth "band". Fourth band which is black and white image in our case was generated from color RGB image.

Using a Fast Fourier Transform Annular Band Approach the input image is converted from spatial domain to frequency domain. This frequency domain image is analyzed for plant identification. The advantage of using Annular Band Approach is rotational invariance. This was important as the plant are not in a fix position [3]. After transforming the image in frequency domain, the power spectrum inside the annular band of radius R1 to R2 is calculated. The center of the image is the center point of the annular band. This user defined band keeps on sliding towards the edge of the image. A plot of power capsulated in the annular band verses radius is plotted. The relative frequency is observed. This relative frequency forms the basis of identification plants [5]. A graph power spectrum verses radius was plotted. One way to analyze spatial variations is the decomposition of an image functions into a set orthogonal functions, one such set being fourier (sinusoidal) functions. The fourier transform may be used to transform the intensity image into the domain of spatial frequency Fig. 9.

Let f(x) be a continuous function of a real variable x. The fourier transform of f(x), denoted by $\mathcal{f}[f(x)]$, is defined by

$$\mathcal{f}[\{f(x)\}] = F(u) = \int_{-\infty}^{\infty} f(x)^{[-j2\pi ux]} dx \qquad (2)$$

where $j=\sqrt{-1}$

If a texture is at all spatially periodic or directional, its power spectrum will tend to have peaks for corresponding spatial frequencies. These peaks can form the basis of features of a pattern recognition discriminator. In this method the fourier space is partitioned in to radial bins. These bins together with fourier power spectrum are used to define features. if F is the fourier transform, the fourier power spectrum is given by $|F|^2$. Radial features are given by

$$V_{r1r2} = \iint |F(u,v)|^2\} dudv \qquad (3)$$

Where the limits of integration are defined by r^2 $|F(u,v)|^2 dudv$, $r^2 \leq u^2$, $v^2 < r^2$, $0 \leq u$.

Where $[r_1,r_2]$ is one of the radial bin and V is the vector defined by different values of r1 and r2. Radial features are co-related with texture coarseness. A smooth texture will have high values of Vr_1r_2 for small radii, where-as a coarse, grainy texture will tend to have relatively higher values for larger radii.

IV. Fractal Dimension

Fractals are a class of mathematical functions which have found use in classification of natural shapes and textures. The fractal dimension D is computed of the black and white plant image. By comparing the fractal dimension of different variety of plants the program identifies the type of plant in the image. Fractal geometry provides both a description and a mathematical model for many of the seemingly complex forms found in nature[10]. Shapes such as coastlines, mountains and clouds are not easily described by traditional Euclidean geometry. Fractals are appropriate with natural shapes they work with recursive algorithm [2]. Generalizing for an object of N parts, each scales down by a ratio r from the whole we get, $Nr^D = 1$ which defines the fractal Dimension D. Where $D = \log N/(\log 1/r)$.

The fractal model is used to relate a metric property such as length of a line or area of a surface to elemental length. For e.g. If the length of a coastline may be determined by placing a 1km ruler end to end along the shoreline. If a 0.5 km ruler is used for the same coast, the measured length will be longer. If the increase in length follows a consistent rule over a range of elemental ruler then it may be called a measure of the coastline's geometrical properties[2]. The functional relationship between ruler size and length is $L(e)=\lambda e^{(1-D)}$.
Where
L(e)= Total length
e = Elemental ruler length
D = Fractal Dimension
λ = Scaling constant.

The model changes only when surfaces are considered.

$$S(e) = \lambda e^{(2-D)} \quad (4)$$

Where S(e) = Surface area. $D\approx 2.00$ implies a smooth planer surface and $D\approx 2.99$ very rough 3D surface.

Since the image is sampled at equal spatial intervals, methods for determining D from continuous functions could not be directly utilized. The surface of the image was considered as a set of rectangular solids with different heights, but with square sides of length e. Thus the surface area was defined as

$$S(e) = \sum_{x,y} e^2 + e[|f(x,y)-f(x+1,y)| + |f(x,y)-f(x,y+1)|] \quad (5)$$

Where f(x,y) is the image intensity function. This implies that the surface area is the sum of the top area plus the area of two sides of each cube for all the cubes in the image. The area was computed for e=1..8. Once the area vs. e data was produced for each image, a linear regression was performed on log(e) vs. log(S(e)) relation. The fractal Model was considered good if the regression co-relation was high. The slope of the line after linear regression gives the fractal dimension of the plant image. If the relationship between x and y co-ordinates appears to be reasonably linear, we can postulate a linear equation which best fits the sample data . We can estimate a and b by using the criterion of least squares of vertical distances from the sample points to the regression line y= a + bx. Fig. 1 shows the Fractal Dimension for the preprocessed images.

Image1	Image2	Image3	Image4	
1.094737	1.157957	1.389290	1.380665	Binary
1.113819	1.064315	1.136459	1.142405	Textured

Fig. 1 Fractal Dimension

V. Co-occurrence Matrix Method

When small image areas from black and white photograph are independently processed by computer, texture and tone are the most important. Gray tone Spatial-Dependence Matrices is calculated from the image. All the textural features are extracted from these gray-tone spatial dependence matrices [6]. The image texture when decomposed has two dimensions gray level primitives or local properties constituting the image texture and spatial organization of the gray level primitives. Gray level primitives includes both its gray level and gray level properties. The image texture can be described as by number, type of primitive and their spatial layout. To make our plant canopy image close to macro texture we segment the image and remove ground information. Texture cannot be analyzed without a frame of reference in which the gray level primitives begin to have distinct organization and shape. So we must start co-relating graylevel-textural are inter-related. In the scanned image gray level and texture sometimes tend to dominate each other. Co-occurrence matrix creates a unified set of operators capable of performing both the global and local analysis tasks. Co-occurrence matrix gives the relative frequency of a transition from each gray level i to the gray level j, given the displacement vector i.e., a type of edge information. Since each co-occurrence matrix is a second order probability distribution, the distribution of gray levels i.e., a normalized gray level histogram can be obtained from each by partial summation. Finally co-occurrence matrices do contain at least some rudimentary shape information. The number of computation required is directly proportional to the number of resolution cells present in the image. In comparison, the number of operations are of the order of nlog(n) if fourier transform is used to extract the textural feature information. Softwarewise, to compute GLC matrix one needs to keep only two lines of image data in core memory at a time which saves storage space. Textural Features Extracted from GLC Matrix

	Image1	Image2	Image3	Image4
Angular Second Moment	0.47	0.65	0.54	0.50
Contrast	0.05	0.08	0.04	0.04
Co-relation	0.90	0.69	0.91	0.92
Variance	1.24	1.13	1.21	1.23
Inverse Difference Moment	0.98	0.96	0.98	0.98
Sum Average	2.80	2.32	2.61	2.73
Sum Entropy	3.71	3.02	3.42	3.58
Sum Variance	8.17	5.55	7.24	7.76
Entropy	0.38	0.30	0.34	0.35
Difference Variance	0.08	0.13	0.07	0.07
Difference Entropy	0.16	0.15	0.17	0.17

Fig. 2 Binary Image1

	Image1	Image2	Image3	Image4
Angular Second Moment	0.33	0.64	0.44	0.38
Contrast	479.04	405.80	44.67	44.75
Co-relation	0.89	0.63	0.93	0.94
Variance	2179.07	550.4	342.82	390.1
Inverse Difference Moment	0.62	0.80	0.77	0.74
Sum Average	69.5	19.44	24.59	28.59
Sum Entropy	72.95	21.18	27.04	31.35
Sum Variance	20747.81	4503.0	3351.0	3831.02
Entropy	1.92	0.93	1.28	1.44
Difference Variance	0.99	0.61	0.59	0.63
Difference Entropy	0	0	0	0

Fig. 3 Binary Image2

VI. CONCLUSION

Three methods were evaluated for identification of different plant species. The Fourier Transform of the preprocessed image was computed. The fourier image in frequency domain was divided in different radial bins from the center of the image. The graphs were plotted between the power spectrum and the radius of the annular bin. The graph of the first two plant images showed a completely different trend which can also be categorized as different signatures in Fig. 11 and Fig. 12. While the other two images which are taken from the same species of plants have a similar trend. The result was similar in the case of the binary and a textured image. To analyze the graph trend software program involving the binary image was faster than textured image. The results were highly depended on the time when the image was grabbed.

Fig. 1 shows the fractal Dimension of all four images. Binary image shows more difference in fractal dimension for different images than textured image. The fractal Dimension for similar image1 and image2 are different while for the similar ones image3, image4 are almost same. The results vary highly if the orientation of the image was changed.

The texture analysis method using the co-occurrence matrix gives promising results and takes less time to compute than the Fourier method. The identification is more accurate if the image gray levels are preserved. However, this is less important with the Fourier method. The table in Fig. 2 and Fig. 3 is the texture parameters extracted from co-occurence matrix from binary and textured images. The table for the different plant species for image1 and image2 is given. The method worked accurately for all the images.

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Fig. 4 Plant1

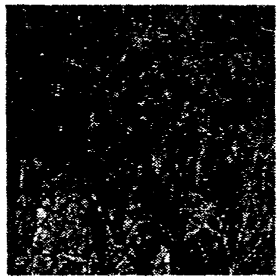
Fig. 5 Plant2


Fig. 6 Plant3


Fig. 7 Segmented plant1


Fig. 8 Filtered Plant1

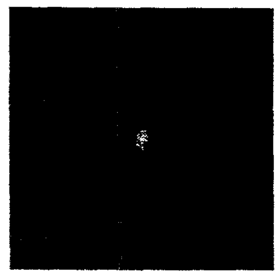
Fig. 9 FFT Plant1

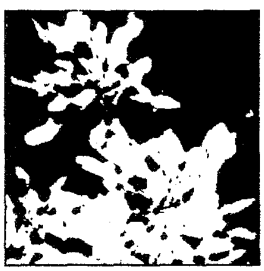
Fig. 10 Binary Plant1

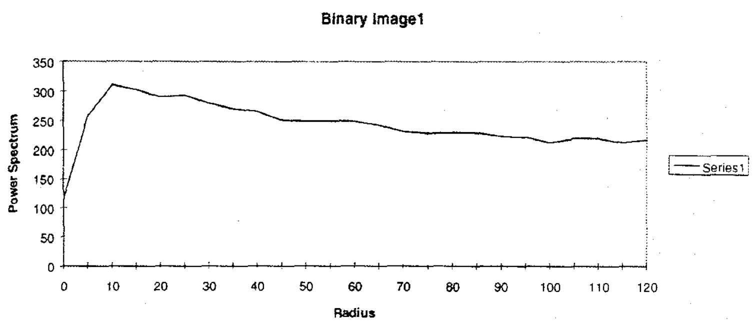

Fig. 11 Frequency Domain Analysis

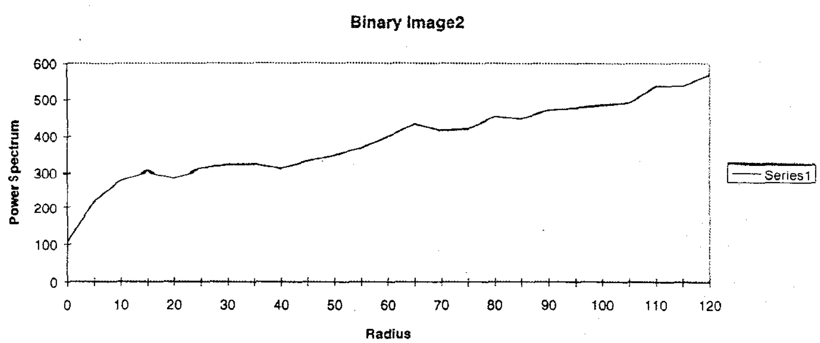

Fig. 12 Frequency Domain Analysis